Essays on Credit Ratings

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Declaration

This is to certify that that the work contained within has been composed by me and is entirely my own work. No part of this thesis has been submitted for any other degree or professional qualification.

Signed:

Abstract

This PhD thesis consists of three independent empirical research papers about credit ratings and the connection between credit ratings and the financial market.

A credit rating agency (CRA) is a third-party financial institution providing assessments and recommendations for other market participants about the performances of firms, the default risk of financial instruments issued by those firms and the credit quality of sovereign countries who issue government debts. On account of the essentiality of information transparency in the modern financial system, the credit rating industry is gaining importance in terms of its role as an information-provider for market participants and of its function to reduce the information asymmetry in the financial market. Due to this significant importance, CRAs may impact the behaviors of market participants by offering signals about the firms or financial instruments and hence have a strong influence on the stability of the financial market. The aim of this PhD thesis is to discuss the relationship between credit ratings and the financial market from three perspectives: the link between sovereign ratings and firm's performances in the context of the European debt crisis, the role of credit ratings in the pricing of asset-backed securities (ABS) before and after the global financial crisis, and the motivation of self-interests of the CRA industry.

In the first empirical paper, I investigate the shock of sovereign downgrades and the association between them with the performances of listed banks which are registered in the downgraded countries. The previous literature shows the connection between sovereign ratings and bank performances and hypothesizes some potential channels (such as the government debt and government guarantee) by which sovereign ratings impact bank performances. Nonetheless, individual bank ratings are neglected in these analyses. I fill in this gap by studying the role of bank ratings in the transmission of effects of sovereign downgrades on bank performances. I find that sovereign rating

downgrades followed by bank rating changes have a stronger impact on the bank stock returns and Z scores (a proxy of the bank insolvency risk) than those which are not followed by bank rating changes. To further tease out the independent effect of sovereign and bank rating downgrades, I take advantage of 'sovereign-ceiling policy' which creates the semi-passive bank rating downgrades when the sovereign rating ceiling has been downgraded. The empirical tests of the banks downgrades triggered by the sovereign ceiling policy help us to conclude that bank rating downgrades provide extra information to the market even if they occur no more than two days after the sovereign ratings are downgraded.

In the second empirical paper, I focus on the ABS market and the role of CRAs in the determination of ABS prices. I investigate whether the reactions of ABS investors to credit ratings have significantly changed since the shock of the global financial crisis. To empirically test the ABS investors' behavior, I run a series of regressions to study the correlation between ABS issuance spread and the issuance credit ratings in pre- and post-crisis periods. I find evidence of a weaker reaction of ABS investors to the ratings offered by credit rating agencies after the financial crisis. To supplement the static-regression analysis, I apply event-analysis methods to identify the ABS price reactions to the rating events in the two periods and identify weaker price reaction degrees after the crisis. The conclusion is that before the 2008 crisis, ABS investors' decisions, reflected by both the issuance spread and transaction prices, were significantly associated with the ratings offered by CRAs while the post-crisis period has seen a weaker link between spread/prices and CRAs' announcements, indicating a smaller influence of CRAs on the ABS market.

The third empirical paper discusses CRA self-interests from the perspective of the association between rating solicitation status and the conservatism as well as the quality of rating services. It contributes the literature by applying the gap between unsolicited and solicited ratings as a measurement to investigate the motivation of

CRAs. Based on a simplified theoretical model, I raise the hypothesis of self-selection to demonstrate the motivation of firms who do not solicit rating services and the rationality of rating agencies' decision to offer ratings with more conservative levels for unsolicited rating recipients. Firms who realize that their future performances will deteriorate are less likely to solicit ratings from rating agencies. Rating agencies capture this signal and offer unsolicited ratings to those firms with a more conservative rating reflecting the self-selection effect. I empirically test this hypothesis using Moody's unsolicited rating data and I obtain two findings. The first finding is that controlling for fundamental factors, Moody's unsolicited ratings are lower than solicited ones. The second finding is that the rating qualities of both types of ratings are not significantly different from each other.

My research contributes to both the academic literature and the practical field of the credit rating industry by providing a comprehensive discussion on the connection between a variety of credit rating services (sovereign ratings, firm ratings and bank ratings) and the market reactions (issuance and transaction prices, insolvency risk and default risk) in different cases (the structured finance products, the sovereign ceiling policy and the issuance of unsolicited ratings). The study also investigates the shock of two recent financial crises (global financial crisis and European debt crisis) on the credit rating industry, which provides suggestive findings for the regulators who are willing to take some actions to intervene in the CRA industry in order to enhance the stability of financial markets in the post-crisis era.

Summary

Credit rating agencies are professional institutions that evaluate the creditworthiness of firms or financial products issued by firms for investors. They play an essential role as the information provider in the financial market to benefit both the lenders and borrowers, in terms of enhancing the communication of information between both sides. However, with the expansion of the market scale of credit rating industry and the financial regulation reforms linking the regulatory requirements with the credit ratings, CRAs have gradually obtained oligopolistic power. The enhancement of such power enables CRAs to influence the market participants' decisions. My thesis consists of three independent essays investigating three issues in the context of this role transformation of credit rating agencies.

The first essay is a study on the relationship among sovereign ratings (for creditworthiness of countries), bank ratings (for creditworthiness of individual banks) and the bank performances. I conclude that sovereign ratings provide additional information for the financial market besides the information which has been provided by the bank ratings. The second study is designed to test the relationship between credit ratings and the prices of Asset-Backed Securities (ABS), an innovative complex financial product. I find that the occurrence of the global financial crisis is associated with a weaker relationship, which implies a weaker market influence of credit rating agencies. In the third paper, I measure the self-interest motivation of credit rating agencies by studying the comparison between the unsolicited ratings, which are not paid by the firms to CRAs, and the solicited ratings which are paid for. I do not find evidence to show that the credit rating agencies issue biased ratings due to their motivation of collecting service fees.

Papers adapted from this thesis

Moreira, F., & Zhao, S. (2018). Do credit ratings affect spread and return? A study of structured finance products. *International Journal of Finance & Economics*, 23(2), 205-217.

Zhao,.S., Moreira, F., & Wang, T. (2016) Have the credit rating agencies learned the lessons from the crisis? An empirical research on the performances of ABS credit rating procedure before, during and after the 2008 crisis. Conference Paper and Presentation at British Accounting & Finance Association (BAFA) Annual Conference, 21th – 23th March 2016, Bath, UK

Zhao,.S., Moreira, F., & Wang, T. (2017) The reliance of structured finance investors on credit rating agencies before and after the financial crisis. Conference Paper and Poster Presentation at 2017 American Economic Association (AEA) Conference, 6th – 8th January 2017, Chicago, US

Zhao,.S., Moreira, F., & Wang, T. (2017) The reliance of structured finance investors on credit rating agencies before and after the financial crisis. Conference Paper and Presentation at Munich International Academic Conference on Business & Economics 2017, 21st-22nd June 2017, Munich, Germany

Zhao,.S., Moreira, F., & Wang, T. (2017) Does the bank rating function as a 'middle man'? An analysis of the relationship among sovereign ratings, bank ratings and bank performances. Conference Paper and Presentation at 2017 Credit Scoring and Credit Control Conference, 31st August – September 1st 2017, Edinburgh, UK

Zhao,.S., Moreira, F., & Wang, T. (2017) ABS market reaction to credit ratings before and after the financial crisis. Conference Paper and Presentation at 2017 Australasian Finance and Banking Conference, 12th -15th December 2017, Sydney, Australia

Zhao,.S., Moreira, F., & Wang, T. (2018) Does the bank rating function as a 'middleman'? An analysis of the relationship among sovereign ratings, bank ratings and bank performances. Conference Paper and Presentation at 2018 Royal Economic Society Conference, 26th – 29th March 2018, Brighton, UK

Zhao,.S., Moreira, F., & Wang, T. (2018) The relationship among sovereign ratings, bank ratings and bank performances, evidence from European commercial banks. Conference Paper and Presentation at 2018 European Financial Management Association (EFMA) Annual Conference, 27th – 30th June 2018, Milan, Italy

Zhao,.S., Moreira, F., & Wang, T. (2018) The relationship among sovereign ratings, bank ratings and bank performances, evidence from European commercial banks. Conference Paper and Presentation at 2018 Financial Management Association (FMA) Annual Conference. 9th - 13th October 2018, San Diego, US

Zhao,.S., Moreira, F., & Wang, T. (2018) Is solicitation status related to rating conservatism and rating quality? Conference Paper and Presentation at 2018 International Conference on Applied Finance, Macroeconomic Performance, and Economic Growth, 20th – 21st October 2018, Hangzhou, China

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List of Abbreviations

ABS	Asset-Backed Security
ADE	Anticipated Dummy of Event
AR	Abnormal Return
BR	Bank Rating
BRD	Bank Rating Downgrade
BRL	Bank Rating Level
CAR	Capital to Asset Ratio
CD	Change Degree
CDO	Collateralized Debt Obligation
CDS	Credit Default Swap
CRA	Credit Rating Agency
DC	During-Crisis
dE	Dummy of Event
D-i-D	Difference-in-Difference
DTD	Distance to Default
EBIT	Earnings before Interest and Taxes
EU	European Union
LR	Letter-Format
MIS	Moody's Investors Service
MBS	Mortgage-Backed Security
NPL	Non-Performing Loan
NR	Number-Format

NRSRO	Nationally Recognized Statistical Rating Organization
PC	Post-Crisis
PIIGS	Portugal, Italy, Ireland, Greece and Spain
PSM	Propensity Score Matching
ROA	Return on Assets
ROAA	Return on Average Assets
S&P	Standard and Poor’s
SAR	Standardized Abnormal Return
SEC	Securities and Exchange Commission
SPV	Special Purpose Vehicle
SR	Sovereign Rating
SRD	Sovereign Rating Downgrade
UDE	Unanticipated Dummy of Event
WAC	Weighted Average Coupon
WAL	Weighted Average Life

1. Chapter I: Introduction

"There are two superpowers in the world today in my opinion. There's the United States and there's Moody's Bond Rating Service. The United States can destroy you by dropping bombs, and Moody's can destroy you by downgrading your bonds. And believe me, it's not clear sometimes who's more powerful."
---Thomas Friedman, PBS Interview, 1996

What is the most valuable 'silver bullet' in the financial industry? For most financial professionals, the answer should be 'information'. For investors (or lenders), it is the access to and the availability of accurate, timely and useful information that determines a successful investment strategy, a profitable financial project or a high-quality market portfolio. For firms (or borrowers), they have to ensure that the information can be clearly and adequately delivered to investors for their projects or entities to have a higher probability of being funded. However, information asymmetry is a significant barrier for both the lending and borrowing sides. The lending side (particularly individual investors) is unable to capture all the useful information of the firms or projects of their interests due to the lack of professional skills or resources. Furthermore, the borrowing side has its self-interested incentive of disclosing positive information and hiding negative information to attract more investors.

Therefore, the aforementioned feature of the blocked channel of information communication between the lending and borrowing sides calls for special institutions which provide expertise to fill in the information gap. The banking industry, as well as other financial institutions such as mutual funds, have reduced the cost of information asymmetry to some extent, by separating the lenders from the borrowers and playing the 'proxy' of lenders to manage their invested money. However, they do not directly disclose the information of invested firms/projects to the investors. Additionally, the financial instruments (loans, stock shares, bonds and other financial products) create new barriers of information communication: the structures, clauses and designs behind these financial instruments are complex and difficult to analyze. In this context, credit rating is one of the most significant industries whose main business is to collect, evaluate and disclose information regarding the quality of financial instruments and financial entities.

My PhD thesis presents my research outcomes in three separate studies about the credit rating industry. The three papers aim to find empirical evidence from three angles (the sovereign ratings, the structured finance product ratings and the unsolicited ratings) to figure out the role transformation of credit rating: from an information provider to a market influencer. In this chapter, I present the background of the CRA's (credit rating agency) role transformation which includes a brief history, the inherent policy support of regulators, the market scale, the phenomenon of oligopoly, the payment model and the complexity of rated financial instruments. Section 1.3 is a summary of my three independent studies. Section 1.4 is a summary of the data and research method and in Section 1.5 I describe the contribution made in the three essays.

1.1 Brief history and the initial function of the credit rating industry

The credit rating industry is one of the industries whose aim is to provide information for investors. A credit rating agency is an institution giving rating opinions to the markets by applying professional risk models to assess the default risks of a financial instrument (security), an institution (firm) or even a country (sovereign). The origin of the rating industry can be traced back to the early 20th century, before which investors themselves assessed the securities' creditworthiness. Because the US railway bond market boomed in the early 1900s, the market was eager to have an information provider who could offer a neutral analysis regarding the quality of those railway bonds. John Moody then published a creditworthiness evaluation for a railway bond, which became the first 'credit rating' product in history (Sinclair, 2014). A brief history of this industry is summarized by White (2010), Sy (2009) and Lynch (2008). The main reason for the origination of the credit rating industry was investors' increasing demand for sufficient information and the ability of specific institutions to provide such information. In other words, the initial function of the credit rating industry was to reduce information asymmetry.

With the development of credit rating industry, investors (i.e. rating users) are relying more on this service in terms of rating accuracy, stability and timeliness (Altman & Rijken, 2004; Cheng & Neamtiu, 2009). However, there is an inherent conflict among those three demands. If the CRAs would like to maintain the stability, they have to sacrifice timeliness by being careful when deciding to change the ratings and vice versa. In order to balance these demands, CRAs invented two special regimes, credit watch and outlook by which they can keep the rating levels constant but express their opinions on the rated firms[1] (Alsakka & ap Gwilym, 2012).

With the rise of growing demand of users for accuracy, timeliness and stability, the recent years see a speedy expansion of the credit rating industry. However, it transpired that the initial aim of the credit rating industry has not been consistently fulfilled concomitant to the development of the rating services, the rapid expansion of modern, complex financial products, and the issuance of a series of rating-based financial regulations. To be specific, credit rating agencies have played the role not only of an information provider, as they should, but also of a market influencer with special powers to influence the market variations, for example, the debt yield (Cantor and Packer, 1996), CDS spreads (Hull et al., 2004; Finnerty et al., 2004) and index options (Tran et al., 2014). Realizing their effects on the market, CRAs try to convince users that they would not negatively impact the market by conducting a 'though-the-cycle' methodologies (Topp & Perl, 2010). However, the transformation of such roles,

[1] A credit watch implies a stronger opinion than an outlook and is issued for a shorter time (3 months for credit watch and 1-2 years for credit rating outlook).

entwined with the potential motivation of the self-interest of rating agencies and the trend of three-party oligopoly, makes both scholars and practitioners concerned about the actual function of this industry. Is it still providing information for investors, as rating agencies themselves claim to be doing, or has it become an obstructer of information transmission by providing biased information for investors due to its interests?

In Section 1.2 I describe the factors that have led to the role transformation of the credit rating industry from an information provider to a market influencer: the regulation effect which makes rating agencies more powerful, the emergence of complex innovative financial products and the huge domestic scale of rating services, the oligopolistic phenomenon of the industry and the issuer-pay model.

1.2 Role transformation of the credit rating industry

1.2.1 The regulation effect

In terms of the regulation effect of credit ratings in the US where all the big three CRAs (Moody's, S&P[2] and Fitch) are registered, some key dates should be noted:

- 1934: The SEC (United States Securities and Exchange Commission) was founded and companies were required to provide standardized financial statements. The ratings' formats were transformed to letter combinations (AAA, AA etc.) and are still used currently;
- 1936: The bank regulators restricted the banks to only invest 'investment-grade' securities. Later on such regulations were imitated by the regulators of insurance companies and pension funds;

[2] S&P: Short for 'Standard and Poor's'

- 1975: The SEC linked the minimum capital requirements on the banking sector to the ratings given by the big three rating agencies, 'crystallizing the centrality of the three rating agencies'.

According to the regulatory policies, the security issuers should get the ratings from the CRAs before they officially issue the securities to the public market. In other words, the regulators gradually 'released' some part of their powers to the Big Three CRAs. The companies who were willing to issue debts and the financial institutions (the servicers or trustees) who serve their clients in the debt issuance process viewed the 'satisfactory' ratings given by CRAs as a special symbol of recognition approved by regulators.

The US financial regulator (SEC) realized that they needed to take actions to monitor the big credit rating agencies given that some power of determining the issuance of financial instruments had been released to them. Therefore, the regulator enhanced the regulations on CRAs through a series of policies:

- 1975: NRSROs ("nationally recognized statistical rating organizations") were introduced and applied by the SEC. Ratings provided by only those agencies approved by regulators as NRSRO are valid as references of debt issuance and capital requirements;
- 2006: The Credit Rating Agency Reform Act 2006 was published. This policy enhanced disclosure requirements and transparency requirements, prohibited CRAs to 'deal with' issuers and emphasized the separation of rating determination departments and fee negotiation departments within an agency in case of conflict of interests etc.;
- 2008: The Dodd-Frank Act was released to restrict CRAs by increasing their costs for issuing biased ratings and partially delinking the minimal requirements of bank-holding securities with the credit rating levels.

However, even with those actions of monitoring the credit rating industry, the malfunction of CRAs was repeated again and again in some historical events, such as the Enron event (2001), the Worldcom (2004) event, the sub-prime mortgage collapse (2007) and the European sovereign crisis (2011).

The effects of regulation on the market impact of credit ratings are discussed in the second chapter of this thesis (the first paper).

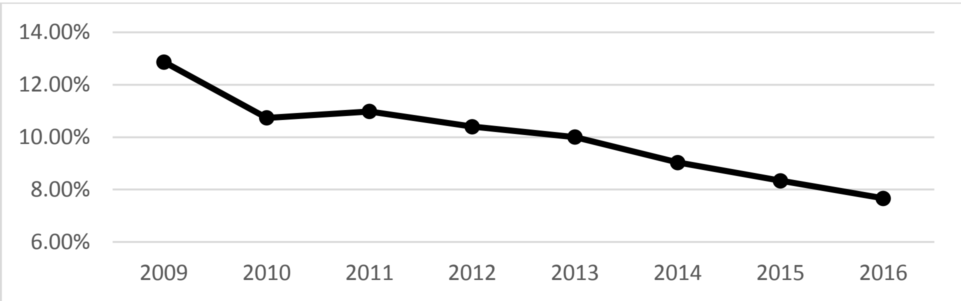
1.2.2 The emergence of complex innovative financial products

Financial practitioners always make every effort they can to create complex structures and contracts for new financial products, such as asset-backed securities (ABS) which were created in the 1970s and expanded with the introduction of the Copula technique (2000). These financial innovations broaden the information gap between investors and issuers since it is difficult for individual investors to have an intuitive feeling or evaluation of the quality of the issuers because the actual indicator of issuer quality has been hidden behind the extremely complex valuation methods, onerous contract clauses or mazy equity structures. Therefore, the investors would rely more on the opinions of CRAs who are viewed as experts in dealing with these financial innovation products. Such reliance of investors enhances the power of CRAs on the financial market and gives them a stronger influence on other market participants.

The third chapter (the second paper) will discuss ABS, an example of the asset securitization products, and its relationship with credit ratings. Structured finance (Asset-Backed Security, also ABS) is an important outcome of the financial innovation in the 20th century. It splits the risks owned by buyers and sellers of a single security by establishing a security pool where payments to investors are based on the incomes of the backing securities (collateralized securities). Different from traditional investment instruments through which the issuers and investors of the securities transact directly, in ABS transactions, an institution called a 'Special Purpose

Vehicle'(SPV) organizes the transactions as a bridge between the specific issuer and the general investors. The investors receive the payments in an order determined by their payment priority reflecting the purchasing prices or spreads (this procedure is called 'tranching' and each of the payment obligations with specific payment priority is called a 'tranche'). Due to the complex procedure of pooling and tranching, investors tend to turn to CRAs for a rating demonstrating its default risk. Despite a decreasing trend of the proportion of ABS ratings among all the entities since the financial crisis (perhaps attributable to the shock of the financial crisis or the restriction of the Dodd-Frank Act issued after the crisis), the percentage has been above 7% since 2009 when the SEC started publishing annual reports on the industry (see Figure 1-1). It shows that the rating services for ABS products take a significant proportion of the whole rating industry, which reflects a large demand for ABS ratings.

Figure 1-1 Percentage of ABS ratings among all the rated entities



Data Source: Annual report on nationally recognized statistical rating organizations (NRSROs) (2009 – 2017)

1.2.3 Market scale, oligopoly and the issuer-pay model

Since the global financial crisis (2007-8), the SEC has published a report each year to disclose the statistics of the credit rating industry in the previous year. According to these reports, I present the number of outstanding credit ratings on the US market from 2009-2016 as well as the proportion of rating dealings provided by the Big Three (Moody's, S&P and Fitch) (Table 1-1).

Table 1-1 Number of Outstanding Credit Ratings on US Market and those issued by the 'Big Three' CRAs

Year	Total No. of	Proportion			
		Moody's	S&P	Fitch	Sum of the Big Three
2009	3,123,748	35.61%	40.18%	21.51%	97.30%
2010	2,816,599	36.90%	42.27%	17.93%	97.09%
2011	2,611,582	38.25%	44.82%	13.35%	96.42%
2012	2,504,584	36.87%	45.65%	13.99%	96.50%
2013	2,437,046	37.01%	46.15%	13.39%	96.55%
2014	2,420,094	34.77%	48.60%	12.44%	95.81%
2015	2,334,600	34.37%	49.13%	13.00%	96.50%
2016	2,285,804	34.17%	48.92%	13.28%	96.37%

Data source: Annual report on nationally recognized statistical rating organizations (2010 – 2017).

Even though the global financial crisis negatively affected the credit rating industry (reflected by a descending number of total outstanding credit ratings), the amount has remained at an extremely high level above two million deals, which means that there are on average over two million entities (including not only firms but also financial instruments and sovereigns) which are rated by CRAs each year. Such a large market scale indicates a common practice in the market of financial entities turning to CRAs for rating services. This provides a necessary condition for the role transformation of the credit rating industry: a big market scale of rating services is accompanied by significant market influence owned by the credit rating agencies, which potentially creates their self-interested motivation rather than the motivation of serving the investors.

In addition, from Table 1-1, it can be observed that the Big Three CRAs took the market share of over 96% from 2009-2017, which is significant evidence of a phenomenon of three-party oligopoly: currently there are hundreds of credit rating agencies in the world but only the three included in Table 1-1 hold a high reputation and take the biggest part of the rating market.

The oligopolistic feature is an essential reason for the existence and maintenance of the 'issuer-pay model' (Utzig, 2010), by which it is the issuers (or the firms who are willing to issue financial products) rather than the investors who pay the service fees to the CRAs. Before the 1970s the rating agencies collected service fees from investors who wanted to see the rating results of the bonds of the investors' interests. The trigger of the transformation from the investor-pay model to the issuer-pay model is the default event of the Penn-Central Railroad Company. The most widely accepted reason is that the previous investor-pay model incurred a free-rider problem which means that after an investor bought the rating, other investors could 'share' it with the buyer with a much lower cost. Another relatively convincing explanation is that with the increasing power implied in a satisfying rating, the issuers had higher incentives to obtain a rating than the investors.(Jiang et al., 2012) However, on the other hand, the increasing fees of rating services is an essential driver of the payment method change because the investors, especially the individual ones, were no longer financially able to pay the rating fees due to a more complex and costly rating procedure conducted by credit rating agencies.

Whatever its reasons are, the transformation of payment model brought up a vested interest group of credit rating agencies whose revenues are collected from only the security issuers but whose rating results influence the entire financial markets. Under the issuer-pay model, the issuers have the motivation to keep more 'stable' ratings for rated firms and hence less timely in terms of identifying their potential risks (Cornaggia and Cornaggia, 2013). In the fourth chapter of the thesis (the third paper), I will conduct a specific study on the link between the rating quality and the fee payment model of the rating services.

Therefore, the huge market scale of the rating market, the oligopolistic position which the Big Three CRAs have and the issuer-pay model with issuers' willingness of being rated higher to finance their projects, collectively determine a predominant power of the big CRAs (Partnoy, 2006).

1.3 Topics of the three essays of the thesis

In the context of the background of the role transformation of CRAs described in Section 1.2, I present three independent studies on the market influence of CRAs in Chapters II, III and IV respectively.

The three chapters aim to answer the following questions:

1) Do sovereign rating actions have a shock on the bank performances in the PIIGS (Portugal, Ireland, Italy, Greece and Spain) countries? Do individual bank downgrades enhance the influence of sovereign downgrades?

2) Do credit ratings (both issuance rating actions and rating changes) have an impact on the prices (issuance spreads and transaction prices) on ABS market? Has such impact declined since the occurrence of global financial crisis (2007-08)?

3) Is the solicitation status of credit ratings associated with the rating qualities? What is the incentive of CRAs to issue lower ratings for the firms who do not pay for the rating services?

Chapter II is the first independent paper, which is designed to test the relationship among sovereign ratings, bank ratings and bank performances. As one of the rating types, a sovereign rating is published by CRAs to evaluate the quality of government debts issued by specific countries. From the perspective of information communication, the sovereign ratings should provide investors with additional useful sources for them to make investment decisions about the firms or financial products in the rated countries. I investigate this function of sovereign ratings by testing whether sovereign downgrades provide additional information for the market besides the information provided by bank rating downgrades which follow these sovereign downgrades. The empirical results I obtain are favorable to the function of sovereign ratings: even after considering the information of bank ratings, I find evidence that sovereign downgrades provide additional information for the market, reflected by the changes in stock prices and Z score (a proxy for bank insolvency). The essential tool I use to tease out the effects of bank ratings and sovereign ratings is the exogenous shock associated with the 'sovereign-ceiling policy'. This policy defines that the bank rating level should not exceed the sovereign rating level of the country where the bank is listed. Therefore, according to this policy, if the bank rating level is equal to the sovereign rating level and the sovereign rating is downgraded afterwards, the bank rating has to be downgraded to obey the policy. This provides an exogenous shock on the downgrades of bank ratings and helps me to specifically measure the additive effect of the following of bank ratings to the sovereign ratings.

In Chapter III, I present the research outcomes of my second study. The study is focused on a type of financial innovation starting in the 1970s, the Asset-Backed Security (ABS), and the relationship between ABS pricing and the credit ratings given to it. As a consequence of the complex payment structure of the ABS products and the difficulty for investors to identify the real lenders of these products, the credit rating is one of the essential components for the ABS to be issued publicly. This enhances the statements I make in Section 1.2, that the strong power of credit ratings transforms the role of CRAs from information provider to market influencer. However, my data analysis results show that after the occurrence of the global financial crisis in 2007-08, the connection between ABS issuance/transaction prices and the levels of credit ratings offered to the ABS product has been weaker than before the crisis. To support the hypothesis of a weaker connection from an empirical perspective, I apply the D-i-D (Difference-in-Difference) technique to compare the variation of prices following credit ratings between the pre- and post- crisis periods. The weaker connection is likely a reflection of several possible factors: the effort of de-linking the regulatory requirements with credit ratings by regulators, the collapse of CRAs' reputation and/or the increasing motivation of the investors to evaluate ABS quality instead of relying on the opinions given by CRAs.

Chapter IV is the third study which is designed to determine the motivation of CRAs to issue unsolicited ratings with no fee payments. The majority of rating services offered by CRAs are solicited ratings and are paid for by the issuers of the financial products. However, the Big Three CRAs offer some unsolicited ratings to the public without being paid for by the issuers. What is the incentive of CRAs to provide those rating services without economic benefits? Do they offer biased lower ratings for those companies who do not pay them in order to 'blackmail' them? By a series of empirical analyses, I find that the reason for a lower rating level for 'non-paying' firms is the 'self-selection' effect of the firms rather than a 'blackmail' effect. Firms with a weak quality are more likely not to request the rating services of CRAs. CRAs observe this and rate them at a lower level without advanced solicitation. I support this finding by studying the actual ex-post performances of the 'paying' and 'non-paying' firms. This finding is favorable to the reputation of CRAs: no evidence is found to show that CRAs deliberately issue lower ratings for the firms who do not pay them; the lower ratings reflect their observation of self-selection effect. It implies that even though CRAs may have their self-interest concerning their profitability, it does not seriously undermine the basic fairness of the services provided by them.

1.4 Summary of research data and methodology

To achieve the research goals described in Section 1.3, I apply empirical research methods using three types of historical financial data: market data, accounting data and rating data.

The market data refers to the issuance or transaction prices of financial instruments. In Chapter II, I use bank stock transaction prices as a reflection of investors' reactions to the rating variations. In Chapter III, the issuance and transaction prices of ABS are collected to measure the market impact of ABS rating changes. In Chapter IV, I use the stock prices as a component of the iteration solution to calculate Distance-To-

Default (DTD), an indicator of the default risk of the firms. The market data are collected from the Bloomberg and Datastream databases. In Chapters II and III, 'stock returns' are used as a measure of market reactions to credit rating actions but the formats of 'stock returns' are different. In Chapter 2, numerical return is taken to measure the stock market variation ($\frac{Price_{t+1}-Price_t}{Price_t}$), with the return of market index is controlled for ($\frac{Index_{t+1}-Index_t}{Index_t}$) but in Chapter III, abnormal return (AR) and standardized abnormal return (SAR) are also calculated to supplement the conventional stock return measures.

The accounting data refers to the quarterly or annual data obtained from the financial reports of listed firms (or banks). It reflects the size, profitability and other fundamental information of the firms and is generally used to test the long-term relationship between firm/security performances and credit ratings. In Chapter II, I collect the basic accounting-based fundamentals of the banks to calculate the Z scores of banks which indicate the insolvency risk. In Chapter III, I use the basic information of ABS deals as control variables to study the link between ABS issuance prices and ABS ratings. In Chapter IV, accounting-based variables are essential components for my use of the iteration technique to obtain the DTD. The accounting data are also collected from the Bloomberg and Datastream databases.

The rating data are the historical rating levels of firms, securities or countries. Currently, the rating notch indicator is formatted as a combination of letters and numbers (or positive and negative signs). For instance, the top level of ratings is AAA for Moody's, S&P and Fitch. The second highest level is Aa1 (Moody's) and AA+ (S&P and Fitch), followed by Aa2 (Moody's) and AA (S&P and Fitch), Aa3 (Moody's) and AA- (S&P and Fitch) and so on. To apply the rating levels in the statistical analysis, I transform their format into numerical style. The details of this transformation are not the same in all the three studies (they are explained in the next three chapters) but the principle is the same: rating levels are transformed into positive integers starting from 1, and a lower number indicates a higher rating level. The data sources of the historical ratings are the Bloomberg database and documents published on CRAs' websites.

1.5 Contributions

My research contributes to the literature of the credit rating industry by providing three empirical studies in the context of the role transformation of CRAs. I find substantial evidence to show a connection between the credit ratings and the market reactions, which suggests that CRAs play the role of a market influencer.

Firstly, I study a couple of categories of ratings. Previous research only focuses on single types of ratings in their research. For example, some of them study the ratings for commercial banks (Richards and Deddouche, 2003, Panetta et al., 2011, Acharya et al., 2014, Alsakka et al., 2014) while others study the ratings for firms in non-financial sectors (Xia, 2014) or special financial instruments (Ashcraft et al., 2011; Fabozzi and Vink, 2012; Mählmann, 2012). However, each of these previous studies only focuses on a restricted scope of the rating industry. In my thesis, I cover all the three types of rating recipients. For firm ratings, I examine not only ratings for general firms (Chapter IV) but also for banks (Chapter II); for security ratings, I investigate the relationship between the rating levels and the prices of stocks (Chapter II) and ABS (Chapter III) to show the market influence of ratings; for countries, the sovereign rating and the relationship between sovereign ratings and firm ratings, as well as the market reactions to both types of ratings are studied (Chapter II).

Furthermore, my research covers different measures of 'market reactions'. In previous research, scholars use stock returns or bond spreads as usual indicators of market reaction to credit ratings (Kaminsky and Schmukler, 2002; Brooks et al., 2004; Durbin and Ng, 2005; Adelino and Ferreira, 2016). Those indicators only cover the information on short-term reactions of secondary market investors but reflect neither the long-term reactions of the market to the rating changes nor the issuance market situations. In my thesis, the measurement of market reaction ranges from short-term indicators such as daily stock prices (Chapter II), ABS issuance and transaction prices (Chapter III) and DTD indicating insolvency risk (Chapter IV), to long-term indicators such as the Z score (Chapter II).

Lastly, my research also involves the rating industry before and after two recent financial crises, the global financial crisis (2007-08) and the European debt crisis (2011-2014). These two recent financial crises have profoundly changed the reputation and market influence of CRAs and hence are non-negligible factors when discussing the credit rating industry. Although a few scholars discuss the change of the credit rating industry after the global financial crisis (Utzig, 2010; White, 2010), most of these studies discuss the reform plan for the rating industry in the post-crisis period from a qualitative perspective. In my thesis I use empirical analyses to investigate the change of CRA activities after the crises. Chapter II studies the sovereign ratings of five European countries (Portugal, Ireland, Italy, Greece and Spain), which experienced a large number of sovereign downgrades during the European debt crisis. Chapter III explores the change in the rating-price link of ABS markets before and after the global financial crisis in 2007-08. I find a weaker relationship between credit ratings and issuance/transaction prices after the financial crisis. This provides a signal for the market that the CRAs have a weaker influence on the market in the post-crisis period.

My research also provides useful information for practitioners in the financial field. For CRAs, the research in my thesis helps them to get a comprehensive knowledge of their role transformation after the global financial crisis. The empirical results about how sovereign ratings, ABS ratings and unsolicited ratings impact the market may help them to improve their function as information providers in the financial market and realize that the new role of market influencers enables them to either provide more transparency for the market or block the information channel due to conflict of interest. For other participants in the financial market (banks and investors), this study may help them empirically measure the impact of CRAs and obtain a deeper understanding about how to react to CRA's opinions. In addition, for financial regulators, my research offers evidence suggesting a call for stricter regulation for the rating industry, especially for those big CRAs who have sufficient power to influence the market and may be sensitive to the profit motivation and conflict of interest.

2. Chapter II Do bank rating changes following sovereign rating changes provide extra information? Evidence from the sovereign-ceiling policy

“The reputation of western credit rating agencies has been questioned for a long time, with the decline of their authority and significance.”

--Comments of the Xinhua News Agency (a Chinese stated-owned news agency) after the announcement of the sovereign downgrades of China released by Moody’s (23 May 2017) and the subsequent downgrades of a number of Chinese commercial/policy banks (Agricultural Bank of China, Bank of Communications Co, Agricultural Development Bank of China, China Development Bank Corporation and the Export-Import Bank of China) a day later (24 May 2017)

2.1 Introduction

The opening quotation of this chapter is a comment from a Chinese state-owned news agency to respond downgrade actions taken by Moody’s for Chinese sovereigns and some of the main commercial banks. This comment seems to contradict the statement in Chapter 1 that the role of CRAs has come to be a market influencer. Therefore, the aim of this chapter is to further explore whether CRAs have an impact on the global market, from a perspective of sovereign ratings and bank ratings.

The literature widely discusses the relationship between sovereign risks and bank performances. Caporale et al. (2012) discuss the relationship between sovereign characteristics and the individual bank performances in each country. Furthermore, to examine and measure the sovereign risk, scholars focus on an essential indicator, the sovereign ratings. As defined, the sovereign rating reflects the credit rating agency’s (CRA) assessment of the government debt’s quality. By its nature, it is not linked to the performances of commercial banks located in the corresponding countries. However, the majority of the literature (Panetta et al., 2011; Correa et al., 2014; Acharya et al., 2014; Brunnermeier et al., 2016; Gibson et al., 2016) observes that sovereign rating significantly impacts bank behaviours and bank performances. They find a significant variation of stock/bond prices which follows the sovereign rating events occurring in corresponding countries. It suggests that investors change their attitudes towards the banks whose countries receive sovereign rating events.

Therefore, the channel by which sovereign ratings affect bank performances is investigated and explored by scholars. The mainstream literature studies the factors related to the governments of countries encountering sovereign rating events and discusses the potential conduits by which government activities may affect the commercial banks; for instance, the government debts held by domestic banks, the quality of government guarantees for banks and so on.

In this paper, I offer another angle, the bank entity ratings, to explain the connection between sovereign ratings and bank performances. The literature discovers two phenomena (Richards and Deddouche, 2004; Williams et al., 2013; Alsakka et al., 2014): sovereign rating actions are very likely to be followed by bank rating actions and bank ratings naturally impact the market performances of the corresponding banks. I combine these two phenomena, consider the potential channel of sovereign ratings' impact on bank performances and show evidence to support the hypothesis that bank ratings play a 'middleman' role by transmitting the sovereign ratings' impact to the bank performances.

In this chapter, I define 'bank performances' from two perspectives: a short-term analysis of stock return shock (on a daily basis) and a long-term analysis of insolvency risk (reflected by Z score on an annual basis).

For analysis on a daily (an annual) basis, I focus on the cases where sovereign rating events and bank rating events occur sequentially with an interval shorter than two transaction days. The reason for choosing those special cases as the analyzed sample is to reflect the relationship between sovereign ratings and bank ratings in an institutional scenario. In the scenario where bank ratings follow sovereign ratings in a short interval, the information provided by the latter may be covered by that offered by the former if bank ratings do not transmit or enhance the impact of sovereign ratings.

In other words, I define ‘the transmission of sovereign rating impact’ by testing whether investors/bankers receive extra information from the bank rating events which follow the sovereign rating events. For the long-term analysis, I focus on rating events occurring within a calendar year to define the scenario that sovereign rating actions are followed by bank rating actions.

The hypothesis is empirically tested based on two sub-hypotheses. The first hypothesis indicates that if a sovereign rating action is followed by a bank rating action, the power of the effects of sovereign rating downgrades on bank performances would be enhanced. In other words, if a change in bank rating follows a sovereign downgrade, the impact on the performances of the corresponding bank is stronger than if the bank ratings did not follow the sovereign downgrades. However, this finding alone does not enable me to conclude that bank ratings act as the channel because the enhancement of power may be derived from the independent impact of the bank rating downgrades rather than the effect of the ‘follow’ of bank ratings to sovereign downgrades.

To examine the ‘channel’ effect, I further explore the first hypothesis by applying an exogenous shock on the bank rating downgrades which are not related to the independent characteristics of the rated banks. I use the sovereign-ceiling policy as the shock, which regulates the CRAs to offer ratings for individual firms at a level not higher than the sovereign ratings in the corresponding countries. According to this policy, if a bank is rated at the same level as the sovereign rating and the sovereign rating is downgraded, the CRA will downgrade the bank rating following the sovereign downgrade to satisfy the requirement of the policy.

Therefore, the second hypothesis is designed to test the effect of sovereign-ceiling policy on the transmission of sovereign rating downgrades’ impact. I empirically test the hypothesis that bank rating downgrades, which follow the sovereign rating downgrades triggered by the sovereign ceiling policy have, on average, a weaker impact on bank performances than other bank rating downgrades following sovereign downgrades but not triggered by the policy. It enhances the hypothesis of channel effect of bank ratings: bank rating downgrades triggered by the sovereign ceiling policy (which can be viewed as passive actions by CRAs) enhance the effect of the sovereign rating downgrades at a lower degree, which shows that the active bank downgrades enhance sovereign ratings downgrades' effect besides their independent impacts.

In this research, I extend the scope of 'bank performances'. The traditional indicator, stock returns, is applied by the mainstream of literature to test the market reaction to rating changes (West, 1973; Hand et al., 1992; Kaminsky and Schmukler, 2002; Brooks et al., 2004; Gibson et al., 2016). I follow this stream of literature by testing the stock returns in ten-day time window after the occurrence of sovereign rating changes. Besides the short-term indicator, some scholars also raise some long-term indicators of the impact of rating changes, for instance, lending strategy and funding strategy (Adelino and Ferreira, 2016), or cross country bank flows (Kim and Wu, 2011). However, I consider that the function of credit ratings is to predict the credit risks of firms or countries. Therefore, a long-term indicator of the credit risk of rated banks is selected to test the power of sovereign ratings. I use a Z score as the indicator of banks' insolvency risk, which is a reflection of the bank credit risk. I further test whether the sovereign ratings have a significant effect on the Z score change in the following year, whether such effect is enhanced by the following of bank ratings and whether the fact that the bank downgrade is triggered by the sovereign ceiling policy is related to a weaker shock.

The structure of this chapter is as follows. Section 2.2 describes the background of the research, states the research questions and related hypotheses regarding my research topic and presents my contributions to the existing literature. In Section 2.3 I describe my sample, the types of sovereign rating downgrades, the considered variables and some essential indicators. Section 2.4 shows the regression models which are designed to test the hypotheses shown in Section 2.2 using the data described in Section 2.3. I also report the empirical results of those regression models and discuss how these results can be interpreted to support the hypotheses concerning the channel effects of bank ratings in the context of sovereign rating downgrades. Section 2.5 concludes this chapter.

2.2 Background, Hypotheses and Contributions

Sovereign risk is an essential factor of observing and studying the performances and behavior of the banking sector (Panetta et al., 2011). Among the diversified measurements of sovereign risk, the sovereign rating is viewed as an essential indicator of the sovereign risk of rated countries.

The sovereign rating, on the one hand, reflects the generalized performances (of all related economic sectors) of a country. On the other hand, it releases information to the market and changes the behavior and performance of specific industries in that country. Previous research investigates how the sovereign ratings impact the economic behaviors or performances from an empirical perspective. These studies not only analyze the single market impact, such as sovereign ratings' effect on bond prices, (Kaminsky and Schmukler, 2002), stock returns (Brooks et al., 2004), CDS spreads (Ismailescu and Kazemi, 2010) and economic cycle (Kaminsky and Schmukler, 2002), but also investigate the cross-country effect (spill-over effect) (Ferreira and Gama, 2007; Arezki et al., 2011; Abad et al., 2018).

The banking industry is one of the sectors which are sensitive to the information released by the sovereign ratings (Gibson et al., 2016). Therefore, scholars focus on the association between the sovereign ratings offered by CRAs to a country, and the reactions of banks which are located, registered or listed in that country. Based on the finding that sovereign ratings are significantly related to the bank performances, the literature discusses the potential channel by which sovereign ratings impact bank performances. The government debt held by commercial banks located in the corresponding countries is regarded as a significant conduit of the impact of sovereign ratings on bank performances (Panetta et al., 2011; Correa et al., 2014; Acharya et al., 2014). During the period of sovereign downgrades, the quality of government debt deteriorates, and it negatively affects the quality of commercial banks who hold a large number of government debts. Moreover, the low quality of government guarantees due to the sovereign rating downgrades are also regarded as a factor to transmit the impact of sovereign ratings to the bank sector (Panetta et al., 2011; Acharya et al., 2014). Government bailout is also a factor which is discussed as a potential channel of sovereign-bank relations (Fratzscher and Rieth, 2015). Davies & Ng (2011) explore the possibility that a value reduction of sovereign bonds held by domestic banks would trigger margin calls by counterparties which makes the situation worse. To summarize the mentioned channels, DeBruyckere et al., (2013) conducted a comprehensive empirical analysis using European banks to show that the validity of sovereign-bank channels is sensitive to three factors: capital buffer, funding structure and the proportion of traditional activities. They also find that government intervention plays an essential role in the channel effect which strongly support the hypothesis that the government guarantee is a significant factor to affect the sovereign-bank channel.

Additionally, the literature mentions some other potential factors, such as the decline of service demands as a consequence of poor fiscal condition (Correa et al., 2014) and the free capital mobility (Brunnermeier et al., 2016).

The cross-country effects of sovereign risks on bank performances are also discussed by many scholars. Alter & Beyer (2014) uses sovereign CDS as an indicator of sovereign risks and find a significant link between Spanish sovereign risks and bank performances in other countries.

However, the majority of the literature does not consider another potential channel, which is the bank rating changes after the sovereign rating changes. Panetta et al. (2011) mention the possibility of bank ratings acting as the channel to enhance the impact of sovereign rating changes on bank performance, but they do not provide detailed discussion and empirical evidence to prove this. Davies & Ng (2011) also raised the potential channel of bank ratings. They believe that the sovereign rating downgrades are followed by the bank rating downgrades and the latter actions increase the funding cost or restrict the market access of commercial banks. Some researchers observe the phenomenon that bank ratings have a high likelihood of following the changes of sovereign ratings (Williams et al., 2013; Alsakka et al., 2014). Others find that bank ratings are followed by variations in bank performances (Richards and Deddouche, 2004). Since the sovereign ratings are followed by bank ratings and the bank ratings impact the performances, it is reasonable to hypothesize that bank ratings partially transmit (or enhance) the power of sovereign ratings to affect the bank performances.

To define the concept of ‘bank performances’, I use two indicators, a short-term one and a long-term one. For the short-term measure, I apply stock returns in a 10-day time window following the sovereign rating events to capture the effect of sovereign ratings. Stock prices reflect the expectation of investors, so the literature uses the stock returns as an essential indicator of firm performances reacting to the rating changes (Hand et al., 1992; Dichev and Piotroski, 2001; Richards and Deddouche, 2003).

For the long-term measure, I take the insolvency risk of banks as the measurement of sovereign rating impact. CRAs design credit ratings as an assessment of the rated entity’s credit risks. For banks, insolvency risk is an essential indication of credit risk. Therefore, the link between sovereign ratings in the current year and the insolvency risk in the following year is regarded as a reflection sovereign ratings’ predictability of bank performances. Specifically, I use the Z score as an indicator of annual bank performances in terms of insolvency risk. Z score is commonly used in empirical papers to measure the probability of banks/bank risk takings (Boyd et al., 2006; Gropp et al., 2013; Ignatowski and Korte, 2014; Anginer et al., 2014; Adhikari and Agrawal, 2016) and insolvency (Strobel, 2011; Lepetit and Strobel, 2013; Lepetit and Strobel, 2015). From a statistical perspective, the Z score is equal to the square of the upper bound of the probability of the event that the sum of ROAA (Return on Average Asset) and CAR (Capital-Asset Ratio) is equal or less than zero (Hannan and Hanweck, 1988). A higher Z score is equivalent to a lower probability of becoming insolvent, which reflects a lower insolvency risk of banks. From a mathematical perspective,

$$Z\ score=(ROAA+\mu(CAR))/(\sigma(ROAA))$$

where $\mu(\cdot)$ and $\sigma(\cdot)$ are the mean and standard deviation respectively.

The principal objective of this research is to investigate whether bank rating (BR) enhances the power of signals released by sovereign rating (SR) downgrades (i.e., whether the BR downgrades provide extra information to the market investors/bankers besides SR downgrades leading them). I focus on the information transmission of SR-BR-Performance conduit by testing whether the information contents of SR downgrades are different in two scenarios:

Scenario 1: SR downgrades with BR downgrades followed;

Scenario 2: SR downgrades without BR downgrades followed.

Based on the definition of bank performances, to achieve my research objective of identifying the channel ‘SR-BR-Performance’, I focus on the impact of SR downgrades on bank stock returns (daily) and Z scores (annually). BR downgrades which occur following SR downgrades are then identified to test whether the SR downgrades in Scenario 1 impact the stock returns/Z scores at a higher degree than those in Scenario 2.

However, this test alone cannot fully tease out the independent effects and enhanced effects of SR and BR. Specifically, for Scenario 1, two types of rating downgrade (SR and BR) occur simultaneously, so it cannot be directly observed whether the gap of effects for Scenario 1 and Scenario 2 is due to the enhancement of the followed bank ratings to the sovereign ratings or the independent effect of the bank ratings.

There are three sources of information to the market for the cases when a bank rating downgrade follows a sovereign downgrade:

Source 1: the information provided by SR downgrades;

Source 2: the information provided by BR downgrades;

Source 3: the information provided by the fact that the SR downgrade is followed by BR.

The information source I am interested in is ‘Source 3’. It indicates the extent by which a following bank rating actions would enhance the effect of SR downgrades. Even if I obtain empirical results showing that SR downgrades fitting Scenario 1 have a greater impact on bank performances than those fitting Scenario 2, I am unable to state whether the enhancement of impact is due to Source 2 or Source 3. To extract the effect of Source 3, I apply an exogenous shock on the follow of BR downgrades to SR downgrades despite the specific bank’s information.

To have a more convincing discussion, I further consider a particular case, sovereign ceiling policy, as the exogenous shock. The sovereign ceiling policy refers to the requirement that the rating level of firms in a country should not exceed the sovereign rating of that country. I acknowledge that the ceiling policy was required as a compulsory action for CRAs until 1997, when Standard & Poors firstly rated firms with a higher level than the sovereign ceiling (Borensztein et al., 2013). Since then, the ceiling policy has become a conventional policy. Although it is arguable whether CRAs have strictly followed the policy, a large body of literature believes that the ceiling policy plays a decisive role in the process of CRAs determining the firm rating levels

(Borensztein et al., 2013; Almeida et al., 2017). Specific for bank ratings, Klusak et al., 2017 apply the case of disclosure of unsolicited rating status to present that the ceiling channel is a significant factor to transmit the influence of sovereign rating actions. Based on this consensus, many scholars apply the ceiling policy as a research tool to study the impact of credit ratings on the market. Their research range from the bond spreads (Durbin and Ng, 2005) to the loan supply (Adelino and Ferreira, 2016).

In this essay, I only consider the rating downgrades rather than upgrades for two reasons. Firstly, rating downgrades have a more significant impact on the market than upgrades. In other words, the market is more sensitive to bad news than to good. (Hand et al., 1992; Dichev and Piotroski, 2001; Drago and Gallo, 2016). The second reason is that only downgrades of SR may trigger the sovereign ceiling policy while upgrades are not related to the policy. According to the ceiling policy, BR has to be downgraded after the SR downgrade occurs if the BR was at the same level with SR before SR was downgraded. Therefore, I further split Scenario 1 into two sub-categories:

Scenario 1: SR downgrades with BR downgrades followed;

Scenario 1.1: SR downgrades which trigger the sovereign-ceiling policy with BR downgrades followed;

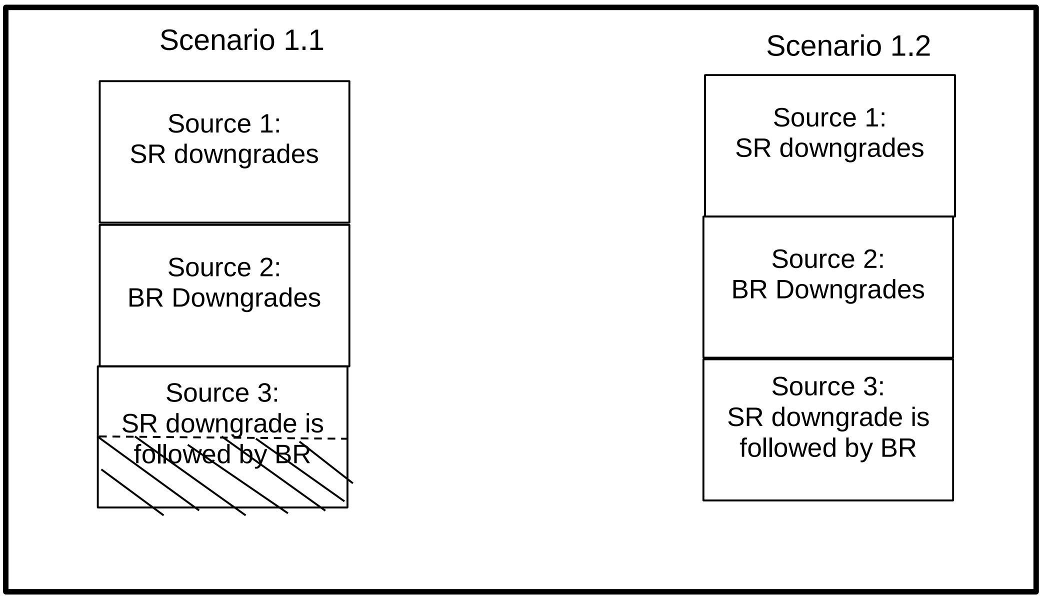
Scenario 1.2: SR downgrades which do not trigger the sovereign-ceiling policy with BR downgrades followed;

Scenario 2: SR downgrades without BR downgrades followed.

The information source decomposition is shown in Figure 1.

Scenario 1.1 should be viewed as semi-passive downgrades while Scenario 1.2 is regarded as fully-active downgrades. Scenario 1.1 (semi-passive downgrades) is associated with only a part of the information of Source 3 because the BR downgrades are announced by the CRA due to the regulation of the sovereign ceiling policy and hence are partially compulsory. Scenario 1.2 (active downgrades) is associated with all the information of Source 3 because the BR downgrades following SR downgrades are not compulsory. Therefore, if the BR following SR provides extra information, the fully-active downgrades should have an impact on stock returns/Z scores at a higher degree than semi-passive ones. In other words, the average gap of market impact on bank performances between Scenario 1.1 and Scenario 1.2 should be significant.

Figure 2-1 Information source decomposition for Scenarios 1.1 and 1.2



For Scenario 1.1, the dash area is excluded because the BR follows the SR due to the sovereign-ceiling policy (semi-passive). Source 3 is not fully active in this case.

To summarize my research objectives, I raise the research questions and corresponding hypotheses as follows.

Question 2-1: Do BRs enhance the power of signals released by SR downgrades?

Hypothesis 2-1: SR downgrades followed by BR downgrades have a stronger association with stock returns/Z scores than SR downgrades not followed by BR downgrades.

Question 2-2: Do active BR downgrades provide extra information to the market besides SR downgrades leading them?

Hypothesis 2-2: Among the SR downgrades followed by BR downgrades, the average association between SR downgrades and stock returns/Z scores is weaker if the BR downgrades are triggered by the sovereign ceiling policy.

My research contributes to the literature as follows.

1. To my knowledge, this study is the first to specifically investigate bank entity ratings as a factor to explain the impact of sovereign ratings on bank performances. The existence of the channel 'SR-BR-Performance' shows that sovereign rating downgrades negatively impact market or management performances of banks partially by the enhancement of bank rating downgrades sequentially. I acknowledge that, even if I show evidence of the bank ratings' role of transmitting and enhancing the effect of sovereign ratings, it does not mean that the bank rating is the sole channel of that. Discussions about other potential channels described by the literature, such as the government debt, government guarantees and financial service demands are still constructive regarding this issue. The way I contribute to the literature is to provide a new angle of entity ratings to explain the 'SR-Performance' link.

2. I consider the case of sovereign-ceiling policy to further tease out the impact of sovereign rating downgrades and bank rating downgrades and solve the problem that the short duration between occurrences of these two types of rating downgrades may contaminate the analysis result. Defining the bank rating downgrades following sovereign rating downgrades triggered by the sovereign ceiling policy as 'semi-passive' and others as 'active', I apply a difference-in-difference analysis to test whether the gap of effects between semi-passive and active downgrades is significant.

3. I extend the scope of 'bank performance', from the short-term indicator (stock returns) to the long-term one (insolvency risk). The short-term impact of sovereign ratings on the stock returns reflects how the secondary market investors react to the

sovereign rating events in a certain period of time. The long-term impact of sovereign ratings on the Z score reflects the predictability of credit ratings in terms of the insolvency risk of banks located in the downgraded countries. I find evidence to show that sovereign ratings have both the short-term and the long-term impacts on bank stock returns and Z scores. The impacts are both enhanced by the follow of bank rating events, which provide extra information both to the investors and on the predictability of insolvency risk.

2.3 Data and Sample

2.3.1 Sample description

I collect the data of historical credit ratings (from Bloomberg), stock prices and accounting information (Thomson Reuters) of listed banks who received ratings by all the Big Three rating agencies (Moody's, S&P and Fitch). Sample banks are those who are registered and listed in five EU countries, PIIGS (Portugal, Italy, Ireland, Greece, and Spain). Since the objective of my research is to study the sovereign rating downgrade events and their effect on bank performances, it is necessary that I have a sufficient number of sovereign rating downgrades in the sample period occurring in the corresponding countries. That is why I filter out countries in the EU other than PIIGS (The sample of PIIGS is also applied by Gibson et al., 2016). The criteria 'rated by the three CRAs', 'listed on the stock market' and 'registered in the PIIGS countries' significantly reduces the number of sampled banks. In addition, to ensure the consistency of my analysis, I filter out the banks which did not exist before 2009 and the banks disappearing (for possible reasons such as M&A or bankruptcy) before 2018. After filtering, I have 25 sample banks. The sample period is Jan 1991-Jan 2018. 1991 is the year when the first downgrade event is observed for the sample banks and 2018 is when the research was conducted. The bank ID, countries, and the number of sovereign rating downgrades by each CRA is shown in Table 2-1.

I observe that the five countries experience a number of sovereign downgrades in the sample period. Greece is the country receiving the greatest number of sovereign downgrades because there are two rounds of debt crises in Greece (2009 and 2015). The numbers of sovereign downgrades are not significantly different among each of the three CRAs. Therefore, in the short-term analysis I do not split the sovereign rating/bank rating downgrades for each of the three CRAs but treat each of them equally in the regressions. However, for the long-term analysis, I run regression separately, using annual rating downgrades for each of the three CRAs because I can only obtain data of Z scores and accounting-based variables on an annual basis and the rating downgrades for each year are difficult to measure when I consider all the three CRAs together. For most of the fiscal years I observe downgrades with different notches for different CRAs so it is more convenient and reasonable to measure the annual rating changes for each CRA separately.

The initial dataset I obtain is in the format of a daily basis and the number of daily observations is 187,550 (25 banks × 7502 days) including missing values (the reason for missing values is that for some dates the bank is not listed or not established) and 176,498 excluding missing values. For the dataset to be run on an annual basis (Z score case) I set a parallel dataset for Z score which has 725 observations (25 banks × 29 years).

Focusing on the sovereign rating events which are fitted to the sample banks, I examine the pair of SRD-Bank (SRD: Sovereign Rating Downgrades), where the sample banks receive sovereign rating downgrades (countries where the banks are registered and listed are downgraded by one of the three rating agencies). For the 25 sample banks, I identify 724 SR changes (both downgrades and upgrades), where 504 are downgrade cases (SRD-Bank).

In the sample of ‘SRD-Bank’ pairs, I further identify the ‘followed by BR’ cases: for the SR changes on the banks, if the bank’s entity rating (issuers’ rating) also changed in the same direction on the same day or one day later, I identify this case as 'followed by BR'. I identify 399 cases both satisfying the 'SRD-Bank' and 'followed by BR'.

The reasons that I choose 'no more than two days' as the criteria to define 'followed by BR' are, 1) for the distribution of duration between sovereign downgrades and bank downgrades shows that most of events occur with an interval shorter than 2 days (see Table 2.2, the ratio is 399/594=79.2%) and 2) if setting a long interval, it would be more difficult to clarify whether bank downgrades actually 'follows' the corresponding sovereign downgrades or they are independent events.

In the sample of 'SRD-Followed by BR', I further identify 'at the ceiling' cases where the BR level was equal to the SR level after the SR changes. For cases satisfying both 'SRD-Followed by BR' and 'at the ceiling', I assume that the rating agencies semi-passively downgrade BRs to maintain the condition that BR should be at a level not exceeding the SR level. I identify 119 cases of 'downgrades triggered by ceiling policy'. Table 2-2 shows the distribution of the identified events.

The number of sovereign downgrades is larger than that of upgrades. This indicates that during the sample period, the situation of sovereign risks of the five countries is deteriorating. It shows that PIIGS has experienced sovereign debt crisis since 2009. For sovereign downgrades, nearly 75% are followed by bank rating downgrades, which shows evidence of a strong link between sovereign ratings and firm ratings (Williams et al., 2013; Alsakka et al., 2014).

Table 2-1 Information of sampled banks and countries in Chapter II

This table shows the country and number of SRD (Sovereign Rating Downgrades) for each of the sample countries (Portugal, Italy, Ireland, Greece and Spain), offered by the three credit rating agencies (Moody's, S&P and Fitch) in the empirical analysis.

Bank Name	Bloomberg ID	Country	No. of SRD		
			Moody's	S&P	Fitch
National Bank of Greece	ETE GA Equity	Greece	14	16	14
Piraeus Bank	TPEIR GA Equity				
Eurobank Ergasias	EUROB GA Equity				
Alpha Bank	ALPHA GA Equity				
Egnatia Bank	EGNAK GA Equity				
Emporiki	TEMP GA Equity				
Banco Santander	SAN SM Equity	Spain	9	8	5
Banco Bilbao Vizcaya Argentina	BBVA SM Equity				
CaixaBank	CABK SM Equity				
Banco de Sabadell	SAB SM Equity				
Bankia	BKIA SM Equity				
Banco Popular Espanol	POP SM Equity				
Bankinter	BKT SM Equity				
Banco Espanol de Credito	BTO SM Equity				
Bank of Ireland	BKIR ID Equity	Ireland	7	7	7
Allied Irish Bank	ALBK ID Equity				
UniCredit	UCG IM Equity	Italy	9	8	7
Intesa Sanpaolo	ISP IM Equity				
Banca Nazionale del Lavoro	BNL IM Equity				
Credito Emiliano	CE IM Equity				
Banca Carige	CRG IM Equity				
Banco Espirito Santo	BES PL Equity	Portugal	7	10	4
Banco Comercial Portugues	BCP PL Equity				
Banco BPI	BPI PL Equity				
Banco Santander Totta	CPDP PL Equity				

It also enhances my motivation for conducting this research: since bank ratings have a very high likelihood of following sovereign ratings, it is possible that sovereign rating downgrades impact bank performances through the channel of bank ratings. For SRD followed by BR downgrades, nearly 30% trigger the sovereign-ceiling policy. The adequate number of cases triggering the policy provides the possibility of conducting a D-i-D analysis on the trigger-policy BR downgrades following SR downgrades and testing whether the semi-passive downgrades have weaker effects on bank performances than active downgrades.

Table 2-2 Distribution of sovereign rating changes in the sample

This table shows the distribution of the identified events according to the types of rating changes. ‘Sovereign Change’ refers to the cases when the country where the sample bank is registered in receives sovereign rating changes by at least one of the three CRAs (Moody’s, S&P and Fitch). ‘BR’ refers to the ‘Bank Ratings’. ‘Ceiling policy’ refers to the ‘sovereign ceiling policy’ according to which the firm rating levels should not be higher than the corresponding country sovereign rating levels.

SovereignChange	724						
		Upgrade	220				
		Downgrade	504				
				Not Followed by BR	105		
				Followed by BR	399		
						Triggered by Ceiling Policy (Semi-Passive)	119
						Not Triggered by Ceiling Policy (Fully Active)	280

2.3.2 Variables in the short-term stock return analysis

The key dependent variables in the short-term analysis and the long-term analysis are stock returns and Z scores respectively.

For daily stock returns, I use time windows from 1 to 10 and another window of 20 days to test the ratings’ effects on short-term market reactions. The selection of time windows (from 1 to 10 days) follows the work by Brooks et al. (2004) and the 20-day window is selected as a benchmark of the decay of shocks’ effect. I recognize that 10-day window may be too long so there may be some contaminated events which would make the results biased. The most significant ‘contaminated events’ are the rating actions by other CRAs so in this section I regard rating events announced by each of the three CRAs as homogenous events.

Based on Hypothesis 1, I expect a significant association between sovereign ratings and stock returns for time windows from 1 to 10 and that the significance recedes or disappears for the time window of 20 days to show that the shock of sovereign ratings on stock prices occurs in a short-term period. For each day (t), I define

$$R_{i,t}[D_1, D_2] = \frac{\text{Price}_{i,D_2} - \text{Price}_{i,D_1}}{\text{Price}_{i,D_1}}$$

D_1 is the starting date of the time window and D_2 is the last day of the time window.

In details, I have a number of combinations of $[D_1, D_2]$:

$R_{i,t}[t-2, t-1]$ which measures the 1-day daily returns before the occurrence of sovereign rating downgrades. The reason that I include the time window before the event in my analysis is to use it as a benchmark and compare the results of 'before-event' return with those of 'after-event' one to intuitively present the shock of sovereign rating downgrades.

$R_{i,t}[t-1, t+T]$ where T are integers ranging from 1 to 10 and 20. It measures the daily returns after the occurrence of sovereign rating downgrades. For each day *t*, I use the last price on day (t-1) as the baseline price instead of the price on the day *t*. The reason is that to study the effect of sovereign rating downgrades on day *t*, I am unable to simply assume that the downgrade announcements are released before, during or after the transaction time of day *t* so it may cause some bias using the prices on the current day as the baseline price. However, if I take the last price on the day before the downgrade announcements as the baseline, the corresponding price returns for period [t-1, t+T] are able to capture the shock of the announcements, regardless of whether the downgrades are announced during the transaction time on day *t*.

This method of measuring stock returns is derived from the work by Kaminsky, G. Schmukler (2002) and Gibson et al., (2016) who use logarithm of stock prices as the indicator of stock price reactions to rating actions. Mathematically, the logarithm of stock prices should have the same implication of the format of stock returns applied in this section.

To control the market conditions, I use the return of stock index in the respective countries in the corresponding time windows.

$$IndexR_{i,t}[D_1, D_2] = \frac{\text{Index}_{i,D_2} - \text{Index}_{i,D_1}}{\text{Index}_{i,D_1}}$$

$Index$ refers to the market index of the country where bank i is registered and listed in. For Greek, Spanish, Irish, Italian and Portuguese banks, I use the ASE (Athens Stock Exchange) General Index, IBEX 35, ISEQ (Irish Stock Exchange) Overall Index, FTSE MIB and PSI (Portugal Stock Index) 20 for the index reference, respectively.

The rating level of sample banks is an essential factor to be controlled for when analysing the effect of sovereign ratings on bank stock returns. I assume that sovereign rating downgrades have different magnitudes of shock on stock prices for banks with different rating levels which have been assigned to the banks. It is reasonable to propose that sovereign ratings have a stronger shock on lower-rated banks because the sovereign risk deterioration may have a greater negative shock on investors' confidence in the banks whose credit condition is worse. Brooks et al., (2004) raised a strategy of categorizing different rating notches into four groups according to 'broad similarities'. Therefore, I categorize the rating levels into four groups: Above AA- (Aa3), AA- (Aa3) to BBB- (Baa3), BBB- (Baa3) to B- (B3) and Below B- (B3)[3]. The reason of categorizing rating levels into the four groups is to consider both the balance of number of observations for each of the groups (I try to keep the differences among the proportions of observations between any two of the groups at a level not larger than 50%) and the implication of the rating levels (Brooks et al., 2004) (BBB- or Baa3 is the threshold of investment/grade classes, B- or B3 is the threshold between 'margin to default' and others so I categorize the rating levels by taking these two specific levels as boundaries). The distribution of daily rating level categories for the sample banks by each of the three CRAs (each observation is a pair of bank-rating on a daily basis) is shown in Table 2-3.

[3] AA-, BBB- and B- are rating indicators applied by Moody's and Aa3, Baa3 and B3 are those applied by S&P and Fitch.

Table 2-3 Rating levels (daily) distribution of the three CRAs

Category of Bank Ratings	Moody's		S&P		Fitch	
	No.	Percentage	No.	Percentage	No.	Percentage
Above_AA- (Aa3)	65416	38.76%	48740	30.00%	74328	51.53%
AA (Aa3) to BBB (Baa3)	73127	43.33%	83801	51.58%	47571	32.98%
BBB- (Baa3) to B- (B3)	17516	10.38%	19999	12.31%	16054	11.13%
Below_B (B3)	12708	7.53%	9917	6.10%	6298	4.37%
Total	168767	100%	162457	100%	144251	100%

As shown in Table 2-3, investment grade levels (Above BBB- or Baa3) take the majority of daily rating observations for all the three CRAs (over 80%). 'Margin to default' ratings take no more than 8% of the sample.

2.3.3 Variable in the long-term analysis on Z scores

As in Lepetit and Strobel (2015), I define Z score, $Z_{i,t}$ (bank *i* in year *t*), as the formula

$$\mathrm{Z}_{i,t} = \frac{\mathrm{ROAA}_{i,t} + \mathrm{CAR}_{i,t}}{\sigma(\mathrm{ROAA})_i}$$

$\mathrm{ROAA}_{i,t}$: return on average assets of bank *i* in year t;

$\mathrm{CAR}_{i,t}$: Capital-Asset ratio of bank *i* in year t;

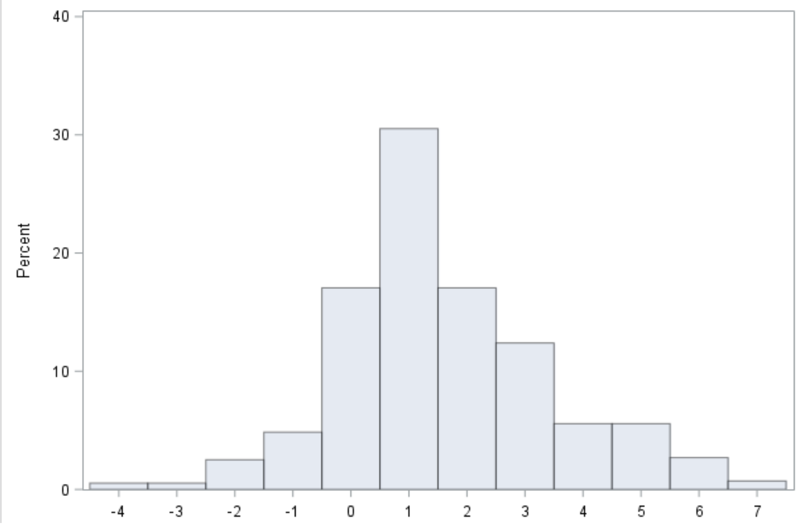
$\sigma(\mathrm{ROAA})_i$: standard deviation of return on average assets of bank *i* in the full period of the sample (1991-2017).

Data is collected from Thomson Reuters.

There are three components in the expression of Z score, ROAA, $\mu(CAR)$ and $\sigma(ROAA)$. Lepetit and Strobel (2015) point out that to make Z score time-varying, each of these three components can be established in different ways, including taking current values, using moving average/variance or full-sample average/variance. In this chapter, I avoid using moving average/variance because the selection of moving length is subjective in existing papers.

The distribution of Z score (annually) is shown in Figure 2-2.

Figure 2-2 Distribution of Z score (annually) for the sample banks



The highest Z score in the sample is 7.226 and the lowest is -4.363. From the perspective of probability, a Z score of 7.226 indicates a probability of insolvency at a level very close to 0 and a Z score of -4.363 indicates a probability of insolvency at a level very close to 100%. The majority of Z scores range from 0 (50% of insolvency risk) to 3 (1.35% of insolvency risk). The shape of the distribution is right-skewed, which means that extreme values concentrate in the range of high-value Z score (low-risk region).

Naturally, the insolvency risk of a bank in the current year is also determined by the accounting behavior of the bank in the previous year. Therefore, a series of accounting-based variables regarding the risk-related performances of banks are collected. These variables control the effects of pre-year performances on the Z scores of the following year. The methods of establishing these variables are applied by Kleinow and Moreira (2016):

Firm Size: the total assets of the banks;

ROA: Return on Assets, an indicator of the profitability of the bank in the previous year;

Non-Performing Loan ratio=$\frac{\text{Non-Performing Loan Volume}}{\text{Total Loan Volume}}$, an indicator reflecting the loss derived from loan credit risks of banks in the previous year;

Deposit Ratio=$\frac{\text{Total Deposit}}{\text{Total Liability}}$ represents the leverage ratio (the capital structure) of banks in the previous year.

2.4 Models and Results

My analyses are conducted in three stages for short-term stock returns and long-term Z scores respectively.

The first stage is to regress the bank performances (stock returns and Z scores) on the indicators of sovereign rating downgrades to present the link between sovereign rating downgrades and bank performances. This stage is the starting point of the entire analysis by showing that sovereign rating downgrades are associated with the bank performances. The regression method of measuring stock return reactions to rating actions was applied by West (1973), Brooks (2004) and Gibson et al (2016). Specifically, the downgrades of sovereign ratings should be followed by a drop in short-term stock prices and a rise in long-term Z scores.

For the second stage, I replace the sovereign rating downgrades by specific SR downgrades which are followed by bank rating downgrades to show whether the sizes of corresponding estimates are bigger than those in the first stage. The rise of estimate sizes indicates that BR downgrades enhance the power of the connection between the leading SR downgrades and the bank performances. That would show evidence for Hypothesis 2-1.

In the third stage, I conduct the D-i-D analysis on the SR downgrades followed by BR downgrades to investigate how the sovereign ceiling policy moderates the effects of SR downgrades on the bank performances. For the D-i-D analysis, the treatment group includes the SR downgrades followed by BR downgrades due to the sovereign ceiling policy. They are also regarded as ‘semi-passive’ downgrades because it is either the credit rating agencies’ decision or the ceiling policy that triggers the individual bank downgrades. The control group includes the SR downgrades followed by BR downgrades not triggered by the sovereign ceiling policy. They are regarded as ‘active’ downgrades because it is entirely the CRAs’ decision to downgrade the individual bank. If Hypothesis 2-2 holds, I expect a result showing that the treatment group has a weaker effect on the bank performances than the control group.

2.4.1 Short-term: daily stock returns (fixed-effect panel regression)

Model 2-1-1: SR downgrades

$$R_{i,t}[D_1, D_2] = \alpha + \beta_{2-1-1} SRD_{i,t} + \gamma_{2-1-1} RIndex_{i,t}[D_1, D_2] + \vartheta_{2-1-1.1} BRL_{i,t} + \vartheta_{2-1-1.2}(BRL_{i,t} \times SRD_{i,t}) + \vartheta_{2-1-1.3} Year_t + \delta_i$$

$R_{i,t}[D_1, D_2]$: daily stock return of bank *i* on day t, in the time window $[D_1, D_2]$. The definition and application of $[D_1, D_2]$ is stated in Section 2.3.2.

$SRD_{i,t}$:dummy equal to 1 if the country where bank *i* listed and registered is downgraded, by one of the three CRAs at day *t* and 0 if else. Corresponding estimate, β_{2-1-1}, captures the stock return changes between one day before and T days after the bank *i* receives a sovereign downgrade.

$RIndex_{i,t}[D_1, D_2]$: daily index return of the market where bank *i* is listed, with the same time window as $R_{i,t}(D_1, D_2)$. γ_{2-1-1} controls the link between the market condition and the stock returns.

$BRL_{i,t}$: dummy variables indicating the average bank rating level (of the big three) of bank *i*. $\vartheta_{2-1-1.1}$ and $\vartheta_{2-1-1.2}$ control the fixed effect of bank levels and the interaction between bank levels and SR downgrades. The aim of adding these two fixed effect controls is to consider different degrees of impact of SR downgrades on stock returns for banks with different credit conditions (reflected by bank rating levels).

$Year_t$: the year of day *t*. $\vartheta_{2-1-1.3}$, controls the time effect (European debt crisis etc.)

δ_i: unobservable heterogeneity of bank *i*.

Descriptive statistics are displayed in Appendix 2-1. The average stock returns are very close to zero (slightly less than 0 but with a relatively large standard deviation) whatever the time windows are. This is reasonable because from the overall perspective, the stock returns should not be significantly larger or smaller than zero in a very long term (over 10 years in this chapter). The numeric average rating level is around 19 (equivalent to level A). It shows that for all the banks in the whole period, average rating level is above the investment grade threshold (BBB).

The result of Model 2-1-1 is shown in Table 2-4.

Estimates on SRD are significantly negative for any $R_{i,t}[t-1, t+T]$ where T range from 1 to 10. Regarding the benchmark window $R_{i,t}[t-2, t-1]$, although I find a negative estimate which shows that the stock return before the event is also negative, its magnitude (-0.63) is much smaller than the estimates for time windows [t-1, t+T] (the sizes are around -4 to -5). This indicates that, compared with the returns before the events, a bank's short-term stock returns are lower after it receives a sovereign rating downgrade. The consistent market reaction does not exist for time window longer than 20 days (The estimate is insignificant for T=20).

The short-term association between SRD and stock returns exists after I control the market index, bank rating level and its interactions with SRD. This result is consistent with the results obtained by other scholars (Brooks et al., 2004; Gibson et al., 2016).

Model 2-1-2: SR downgrades followed by BR downgrades

$$R_{i,t}[D_1, D_2] = \alpha + \beta_{2-1-2.}SRD\_Followed\_By\_BRD_{i,t} + \gamma_{2-1-2}RIndex_{i,t}[D_1, D_2] + \vartheta_{2-1-2.1}BRL_{i,t} + \vartheta_{2-1-2.2}(BRL_{i,t} \times SRD\_Followed\_By\_BRD_{i,t}) + \vartheta_{2-1-2.3}Year_t + \delta_i$$

$SRD\_Followed\_By\_BR_{i,t}$: dummy equal to 1 if the bank *i* receives sovereign downgrades which are followed by the bank rating downgrades (at the same day, or after 1 day) on day *t* and equal to 0 else;

The estimate on the $SRD\_Followed\_By\_BRD_{i,t}$ captures the relationship between specific sovereign rating downgrades followed by bank rating downgrades and stock returns. The result is shown in Table 2-5.

The estimates are insignificant for the time window [t-2, t-1] while those are consistently significantly negative for [t-1, t+T], which shows that SR downgrades are followed by a drop of stock prices within the 10-day time window (even in 20 days).

Additionally, if I compare the size of estimates of parameters on SR downgrades in Model 2-1-1 and Model 2-1-2, I find a significant trend that the sizes in Model 2-1-2 are always larger than those in Model 2-1-1 for [t-1,t+T]. This shows evidence that the degree of stock price

Table 2-4 Regression of Stock Returns on Sovereign Rating Downgrades

This table shows the regression result of Model 2-1-1. The regression is run on the basis of daily bank-rating pairs. Sample banks are the listed commercial banks in the PIIGS countries (Portugal, Italy, Ireland, Greece and Spain). The dependent variable is the stock returns of the time windows [t-2, t-1] and [t-1, t+T] (T=1 to 10 and 20), where the first component is the starting day of the time window and the second component is the last day of the time window and day t indicates the day of the corresponding transaction day. The key independent variable is SRD (Sovereign Rating Downgrades), dummy equal to 1 if the country where bank i listed and registered is downgraded, by one of the three CRAs on day t and 0 if else. Index Return is the daily index return of the market where bank i is listed, with the same time window as the dependent variable. Year and Firm fixed effects are controlled. The fixed effect of bank rating levels and the interaction between bank rating levels and SR downgrades are also controlled. Figures in the brackets are corresponding t-statistics.
N refers to the number of banks and T refers to the number of observations for each of the banks in the panel regression.
*** 1% significance level
** 5% significance level
* 10% significance level

Time window [Starting day, Last day]	[t-2, t-1]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]	[t-1, t+7]	[t-1, t+8]	[t-1, t+9]	[t-1, t+10]	[t-1, t+20]
SRD[a]	-0.63***	-4.08***	-4.22***	-4.06***	-3.87***	-3.99***	-4.72***	-4.84***	-4.97***	-5.22***	-4.37***	-0.69
	(-2.96)	(-13.11)	(-10.95)	(-9.01)	(-7.66)	(-7.16)	(-7.81)	(-7.51)	(-7.32)	(-7.35)	(-5.89)	(-0.99)
Index Return	1.02***	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.10***	1.10***	1.12***
	(291.22)	(289.25)	(291.40)	(290.62)	(289.70)	(288.79)	(288.36)	(288.59)	(290.30)	(292.02)	(293.15)	(303.04)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Rating Level (BRL) Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BRL*SRD Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	31.27%	31.14%	31.51%	31.47%	31.40%	31.35%	31.35%	31.47%	31.82%	32.17%	32.43%	34.76%
N	25	25	25	25	25	25	25	25	25	25	25	25
T	7500	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491	7482

a: The actual coefficients are those figures shown in the table times 10^{-3}

decreases is larger if the sovereign rating downgrades are followed by bank rating downgrades.

Model 2-1-3: D-i-D analysis of BR downgrades triggering the ceiling policy

In this section of analysis, I focus on the cases of SRD followed by BR downgrades and identify scenarios where the BR downgrades occur when the SRD triggers the sovereign ceiling policy (the semi-passive followed BR downgrades).

$$\begin{aligned} R_{i,t}[D_1, D_2] \ = \alpha + \beta_{2-1-3.1} \times SRD\_Followed\_By\_BRD_{i,t} + \beta_{2-1-3.2} At\_Ceiling_{i,t} \\ + \beta_{2-1-3.3}(SRD\_Followed\_By\_BRD_{i,t} \times At\_Ceiling_{i,t}) \\ + \gamma_{2-1-3} RIndex_{i,t}[D_1, D_2] + \vartheta_{2-1-3.1} BRL_{i,t} + \vartheta_{2-1-3.2} BRL_{i,t} \\ \times SRD\_Followed\_By\_BRD_{i,t} + \vartheta_{2-1-3.3} Year_t + \delta_i \end{aligned}$$

$At\_Ceiling_{i,t}$: dummy equal to 1 if the bank rating level of bank *i* is equal to the sovereign rating level at day *t* and 0 else. $\beta_{1.3.3}$, the estimate on interaction term,$(SRD\_Followed\_By\_BRD_{i,t} \times At\_Ceiling_{i,t})$, is the D-i-D estimate which captures how the sovereign ceiling policy moderates such effect. The result is shown in Table 2-6.

$\beta_{2-1-3.3}$ is significantly positive for most of the T (excluding T=3,4 and 5). Since the estimates on SRD ($\beta_{2-1-3.1}$) are negative, the positive sign of D-i-D estimators shows that the treatment group which includes the SRD, followed by BR downgrades to obey the rule of the sovereign ceiling policy, has a weaker stock return effect than the control group (SRD followed by BR downgrades not triggering the policy). The finding shows that SRDs followed by semi-passive BR downgrades are associated with a weaker stock return reaction than those followed by active BR downgrades. This is consistent with Hypothesis 2-2 and indicates that the information provided by the follow of BR downgrades to SR downgrades is significant besides the information provided by the independent effect of BR downgrades.

Table 2-5 Regression of Stock Returns on Sovereign Rating Downgrades which are followed by Bank Rating Downgrades

This table shows the regression result of Model 2-1-2. The regression is run on the basis of daily bank-rating pairs. Sample banks are the listed commercial banks in the PIIGS countries (Portugal, Italy, Ireland, Greece and Spain). The dependent variable is the stock returns of the time windows [t-2, t-1] and [t-1, t+T] (T=1 to 10 and 20), where the first component is the starting day of the time window and the second component is the last day of the time window and day t indicates the day of the corresponding transaction day. The key independent variable is SRD_Followed by BRD (Sovereign Rating Downgrades followed by Bank Rating Downgrades), dummy equal to 1 if the bank i receives sovereign downgrades which are followed by the bank rating downgrades (at the same day, or after 1 day) on day t and equal to 0 else. Index Return is the daily index return of the market where bank i is listed, with the same time window as the dependent variable. Year and Firm fixed effects are controlled. The fixed effect of bank rating levels and the interaction between bank rating levels and SR downgrades are also controlled. Figures in the brackets are corresponding t-statistics.

N refers to the number of banks and T refers to the number of observations for each of the banks in the panel regression.

*** 1% significance level

** 5% significance level

* 10% significance level

Time window [Starting day, Last day]	[t-2, t-1]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]	[t-1, t+7]	[t-1, t+8]	[t-1, t+9]	[t-1, t+10]	[t-1, t+20]
SRD_Followed by BRD[a]	-0.35	-5.38***	-5.70***	-6.01***	-5.83***	-5.87***	-5.23***	-5.43***	-5.36***	-5.71***	-5.16***	-2.16**
	(-1.50)	(-15.69)	(-13.43)	(-12.11)	(-10.43)	(-9.57)	(-7.86)	(-7.66)	(-7.17)	(-7.30)	(-6.31)	(-2.02)
Index Return	1.02***	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.10***	1.10***	1.12***
	(292.21)	(289.32)	(291.49)	(290.70)	(289.78)	(288.79)	(288.38)	(288.61)	(290.31)	(292.04)	(293.17)	(303.05)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Rating Level (BRL) Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BRL*SR Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	31.27%	31.17%	31.53%	31.49%	31.42%	31.35%	31.36%	31.47%	31.82%	32.17%	32.43%	34.76%
N	25	25	25	25	25	25	25	25	25	25	25	25
T	7500	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491	7482

a: The actual coefficients are those figures shown in the table times 10^{-3}

Table 2-6 Regression of Stock Returns on Sovereign Rating Downgrades which are followed by Bank Rating Downgrades (triggered by Ceiling Policy or not)

This table shows the regression result of Model 2-1-3. The regression is run on the basis of daily bank-rating pairs. Sample banks are the listed commercial banks in the PIIGS countries (Portugal, Italy, Ireland, Greece and Spain). The dependent variable is the stock returns of the time windows [t-2, t-1] and [t-1, t+T] (T=1 to 10 and 20), where the first component is the starting day of the time window and the second component is the last day of the time window and day t indicates the day of the corresponding transaction day. The key independent variables include: SRD_Followed by BRD (Sovereign Rating Downgrades followed by Bank Rating Downgrades), dummy equal to 1 if the bank i receives sovereign downgrades which are followed by the bank rating downgrades (on the same day, or after 1 day) on day t and equal to 0 else; At_Ceiling, dummy equal to 1 if the bank rating level of bank i is equal to the sovereign rating level on day t and 0 else and the interaction term between SDR_Followed_by_BRD and At_Ceiling. Index Return is the daily index return of the market where bank i is listed, with the same time window as the dependent variable. Year and Firm fixed effects are controlled. The fixed effect of bank rating levels and the interaction between bank rating levels and SR downgrades are also controlled. Figures in the brackets are corresponding t-statistics.

N refers to the number of banks and T refers to the number of observations for each of the banks in the panel regression.

*** 1% significance level ;** 5% significance level ;* 10% significance level

Time window [Starting day, Last day]	[t-2, t-1]	[t-1, t+1]	[t-1, t+2]	[t-1, t+3]	[t-1, t+4]	[t-1, t+5]	[t-1, t+6]	[t-1, t+7]	[t-1, t+8]	[t-1, t+9]	[t-1, t+10]	[t-1, t+20]
SDR_Followed by BR	-0.002	-0.064***	-0.066***	-0.062***	-0.061***	-0.062***	-0.064***	-0.067***	-0.068***	-0.066***	-0.065***	-0.006
	(-1.04)	(-25.04)	(-20.73)	(-16.72)	(-14.52)	(-13.46)	(-12.83)	(-12.63)	(-12.10)	(-11.27)	(-10.56)	(-0.85)
At the Ceiling	0.031***	0.042***	0.070***	0.098***	0.100***	0.101***	0.043***	-0.0004	0.005	0.004	-0.032**	-0.041*
	(6.92)	(6.46)	(8.73)	(10.46)	(9.56)	(8.75)	(3.42)	(-0.03)	(0.25)	(0.27)	(-2.06)	(-2.04)
SDR_Followed by BR $*$ At the Ceiling	-0.032***	0.039***	0.015*	0.017	-0.023*	-0.022	0.039***	0.038***	0.078***	0.063***	0.012***	0.040*
	(-6.26)	(5.21)	(1.65)	(1.57)	(-1.94)	(-1.64)	(2.73)	(5.44)	(4.80)	(4.32)	(6.32)	(1.83)
Index Return	1.02***	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.10***	1.10***	1.12***
	(291.19)	(292.55)	(291.82)	(290.90)	(289.98)	(289.05)	(288.56)	(288.79)	(290.47)	(292.16)	(293.29)	(303.05)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Rating Level (BRL) Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BRL*Followed Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	31.27%	31.67%	31.69%	31.60%	31.50%	31.44%	31.42%	31.53%	31.87%	32.22%	32.48%	34.76%
N	25	25	25	25	25	25	25	25	25	25	25	25
T	7500	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491	7482

a: The actual coefficients are those figures shown in the table times 10^{-3}

2.4.2 Long-term: Z scores (fixed-effect panel regression)

Observations in the analysis of this section are on an annual basis but the rating changes occur on a daily basis. Therefore, I consider the rating level gaps (SR and BR) between the end and the beginning of each year as a proxy of 'annual rating change'. Rating changes (i.e. SR downgrades, BR downgrades, the trigger of ceiling policy) are identified, measured and considered for each of the Big Three CRAs separately.

The model set of Z score analysis is parallel to that of stock return analysis.

Model 2-2-1: The association between SR downgrades and Z score

$$Z_{i,t+1} = \alpha + \beta_{2-2-1}SRD_{i,t} + X'_{i,t}\gamma_{2-2-1} + \delta_i$$

$Z_{i,t+1}$ is the Z score of bank *i* in the year *(t+1)*;

$SRD_{i,t}$ dummy equal to 1 if the sovereign rating of bank *i* is downgraded in year t and 0 else. The corresponding estimate, β_{2-2-1} captures the association between sovereign downgrades in a year and the change of Z scores in the following year.

$X'_{i,t}$: vector of accounting-based control variables (total assets, return on assets, capital ratio, NPL (Non-performing Loan) ratio and deposit ratio). γ_{2-2-1} is the group of estimates on each of the control variables.

δ_i: unobservable heterogeneity of bank *i*.

Model 2-2-2: The association between SR downgrades followed by BR downgrades and Z score

$$Z_{i,t+1} = \alpha + \beta_{2-2-2}SRD\_Followed\ By\ BRD_{i,t} + X'_{i,t}\gamma_{2-2-2} + \delta_i$$

$SRD\_Followed\ By\ BRD_{i,t}$, dummy variable equal to 1 if the sovereign rating of bank *i* is downgraded in year *t* and the bank rating of bank *i* during year *t* changes in the same direction with sovereign rating changes and 0 else. Corresponding estimate, β_{2-2-2} captures the association between specific sovereign downgrades, which are followed by BR downgrades, in a year and the change of Z scores in the following year.

Model 2-2-3 D-i-D analysis of BR downgrades triggering the ceiling policy

$$Z_{i,t+1} = \alpha + \beta_{2-2-3.1} SRD\_Followed\ By\ BRD_{i,t} + \beta_{2-2-3.2} At\_Ceiling_{i,t} + \beta_{2-2-3.2}(SRD\_Followed\ By\ BR_{i,t} \times At\_Ceiling_{i,t}) + X'_{i,t}\gamma_{2-2-3} + \delta_i$$

$At\_Ceiling_{i,t}$: dummy variable equal to 1 if the rating level of sovereign rating of the country where bank *i* is registered and listed is the same as the rating level of bank rating of bank *i* at the end of year *t*, and equal to 0 if else.

$\beta_{2-2-3.2}$, the coefficient on the interaction term plays the role of D-i-D estimate which captures the effect of the sovereign ceiling policy on the link between sovereign rating downgrades and the Z scores.

I do not find previous papers which regress Z scores to credit rating variables, but the Z score is widely used as an indicator of bank risks by recent research (Chiaramonte et al., 2016; Li et al., 2017).

For Models 2-2-1 , 2-2-2 and 2-2-3, due to the mismatch of data frequency between the daily rating-based variables (SRD, $SRD\_Followed\ By\ BRD_{i,t}$ and $SRD\_Followed\ By\ BR_{i,t} \times At\_Ceiling_{i,t}$) and the annual accounting-based variables (Z score, and control variables), I have to transform the rating-based variables into an annual format (i.e. measuring the rating change in whole years instead of within single days). I acknowledge that this is inconsistent with the tests for stock-return case and may introduce noises into the regressions.

Results of Models 2-2-1 are shown in Table 2-7. Results of Models 2-2-2 and 2-2-3 are shown in Table 2-8. Empirical results show that estimates on *SRD* and *SRD_Followed_by_BRD* in Models 2-2-1 and 2-2-2 are significantly negative. It means that sovereign rating downgrades, when followed by bank rating downgrades, are associated with a lower value of Z score (a higher risk of insolvency) in the following year. It indicates that sovereign ratings have predictability on the future insolvency risk of banks registered in the corresponding countries.

Comparing the sizes of estimates in Model 2-2-2 with those in Model 2-2-1, I find that sizes in Model 2-2-2 are greater than 2-2-1. This offers evidence that, on average, the link between SR downgrades and the rise of insolvency risk is stronger if the SR downgrades are followed by BR downgrades.

For Model 2-2-3, I find significantly positive D-i-D estimates on the interaction term. Since $\beta_{2-2-3.1}$, the estimates on *SRD_Followed by BRD*, is negative, the positive sign of estimates on interaction term means that the treatment group (BR downgrades triggered by the sovereign ceiling policy) is associated with a smaller size of *SRD_Followed by BRD* estimates than the control group (BR downgrades not triggered by the sovereign ceiling policy). This indicates that SRD followed by semi-passive BR downgrades have a weaker impact on Z score than that followed by active BR downgrades. This is consistent with the Hypothesis 2-2 and indicates that the extra information is provided by the fact that bank downgrades follow sovereign downgrades beyond the information provided by the independent effect of BR downgrades.

Estimates on the control variables show the link between insolvency risk and bank fundamentals. From Table 2-7, I find that a lower Z score (a higher insolvency risk) is associated with a larger bank size, a lower return on assets, a higher NPL ratio and a higher deposit ratio.

To summarize the findings of both the short-term and long-term analyses, I describe the main empirical results as follows.

Sovereign rating downgrades are associated with the drop of stock returns within a 10-day time window and the rise of the insolvency risk of banks listed in the corresponding countries in the following year. Model 2-1-1 and Model 2-2-1 both support the statement by reporting significantly negative estimates of sovereign rating downgrades. This finding enhances the conclusions drawn by other scholars who find a strong link between sovereign ratings and bank performances and raise hypotheses based on this link (Panetta et al., 2011; Correa et al., 2014; Acharya et al., 2014; Gibson et al., 2016). The next empirical result shows that specific sovereign rating downgrades followed by bank rating downgrades have a greater impact on stock returns than those not followed by bank rating downgrades. This finding is reflected by estimates on sovereign rating downgrades in Model 2-1-2 and Model 2-2-2 with a larger size than the estimates in Model 2-1-1 and Model 2-2-1. This shows initial evidence of the role of bank ratings played in the transmission of sovereign downgrades' relationship with stock returns and Z scores. The existence of followed bank rating downgrades is statistically associated with a stronger relationship between stock returns and Z scores and sovereign rating downgrades. However, I am unable to conclude that bank ratings' following is a factor in enhancing the effect of sovereign downgrades because sovereign rating downgrades and following bank rating downgrades usually occur in a very short time interval. The enhancement of market reaction and Z score variation may be a consequence of the independent effect of bank rating downgrades but not due to the fact the bank rating downgrades occur following a sovereign rating downgrade. Therefore, I further split the sample of sovereign rating downgrades followed by bank rating downgrades into two groups according to whether or not they trigger the sovereign-ceiling policy.

Table 2-7 Regression of Z scores on Sovereign Rating Downgrades

This table shows the regression result of Model 2-2-1. The regression is run on the basis of annual bank-rating pairs. Sample banks are the listed commercial banks in the PIIGS countries (Portugal, Italy, Ireland, Greece and Spain). The dependent variable is the Z score in the year (t+1). The Z score of year t is calculated by the formula $\frac{\mathrm{ROAA}_{i,t}+\mathrm{CAR}_{i,t}}{\sigma(\mathrm{ROAA})_i}$. ROAA refers to the return on the average assets; CAR refers to the capital-asset ratio and $\sigma(\mathrm{ROAA})$ refers to the standard deviation of return on average assets of bank i in the full period of sample (1991-2017). The key independent variable include: SDR (Sovereign Rating Downgrades), dummy equal to 1 if the sovereign rating of bank i is downgraded in year t and 0 else. Control variables include: Firm Size, the total assets of the firm, RoA, the return on assets, NPL (Non-performing Loan) ratio and Deposit Ratio. Firm fixed effects are controlled. The regressions are run separately for rating changes announced by Moody's, S&P and Fitch. Figures in the brackets are corresponding t-statistics.

N refers to the number of banks and T refers to the number of observations for each of the banks in the panel regression.

*** 1% significance level

** 5% significance level

* 10% significance level

Model	2-2-1		
Rating Agency	Moody	S&P	Fitch
SRD	-0.988***	-0.705***	-0.814***
	(-9.05)	(-7.23)	(-6.93)
Firm Size	-0.011***	-0.010***	-0.010***
	(-4.21)	(-3.82)	(-3.70)
RoA	0.086***	0.111***	0.104***
	(3.40)	(4.35)	(4.00)
NPL Ratio	-0.503*	-0.431	-0.273*
	(-1.72)	(-1.44)	(-1.88)
Deposit Ratio	-0.010**	-0.008*	-0.005**
	(-2.21)	(-1.66)	(-1.99)
Firm Fixed Effect	Yes	Yes	Yes
R2	78.81%	77.75%	77.08%
N	29	29	26
T	25	25	25

Table 2-8 Regression of Z scores on Sovereign Rating Downgrades followed by Bank Rating Downgrades (triggered by the ceiling policy or not)

This table shows the regression result of Models 2-2-2 and 2-2-3. The regression is run on the basis of annual bank-rating pairs. Sample banks are the listed commercial banks in the PIIGS countries (Portugal, Italy, Ireland, Greece and Spain). The dependent variable is the Z score in the year (t+1). The Z score of year t is calculated by the formula $\frac{\mathrm{ROAA}_{i,t}+\mathrm{CAR}_{i,t}}{\sigma(\mathrm{ROAA})_i}$. ROAA refers to the return on the average assets; CAR refers to the capital-asset ratio and $\sigma(\mathrm{ROAA})$ refers to the standard deviation of return on average assets of bank i in the full period of sample (1991-2017). The key independent variable include: SRD_Followed_by_BRD (Sovereign Rating Downgrades followed by Bank Ratings), dummy variable equal to 1 if sovereign rating of bank i is downgraded in year t and the bank rating of bank i during year t changes in the same direction with sovereign rating changes and 0 else; At_Ceiling, the dummy variable equal to 1 if at the end of year t the rating level of sovereign rating of the country where bank i is registered and listed is the same as the rating level of bank rating of bank i, and equal to 0 if else and the interaction term between SRD_Followed_by_BRD and At_Ceiling. Control variables include: Firm Size, the total assets of the firm, RoA, the return on assets, NPL (Non-Performing Loan) ratio and Deposit Ratio. Firm fixed effects are controlled. The regressions are run separately for rating changes announced by Moody's, S&P and Fitch. Figures in the brackets are corresponding t-statistics.
N refers to the number of banks and T refers to the number of observations for each of the banks in the panel regression.
*** 1% significance level
** 5% significance level
* 10% significance level

Model	2-2-2			2-2-3		
Rating Agency	Moody	S&P	Fitch	Moody	S&P	Fitch
SRD_Followed by BRD	-1.064** (-8.35)	-1.030*** (-8.27)	-0.967*** (-5.75)	-0.981*** (-7.53)	-1.102*** (-8.18)	-1.422*** (-7.39)
At_Ceiling	--	--	--	-0.039 (-0.29)	-0.325* (-1.78)	-0.320** (-2.08)
SRD_Followed by BRD * At_Ceiling	--	--	--	0.575** (2.31)	0.428* (1.63)	0.571** (2.03)
Accounting-Based Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R2	79.41%	79.82%	78.36%	79.60%	80.91%	80.50%
N	29	29	26	29	29	26
T	25	25	25	25	25	25

For bank rating downgrades following sovereign rating downgrades, those who trigger the sovereign ceiling policy (semi-passive) have a weaker relationship with the stock returns than those who do not trigger it (active). This finding is obtained by observing significantly positive D-i-D estimates in Model 2-1-3 and Model 2-2-3. The observation of a significant effect of sovereign-ceiling policy on the credit rating determination is consistent with the conclusions by Borensztein et al. (2013) and Almeida et al. (2017). As an exogenous shock on the occurrence of bank rating downgrades which follow sovereign rating downgrades, the sovereign ceiling policy helps me to tease out the 'follow' effects from the effects of independent bank downgrades. I find that semi-passive bank rating downgrades following sovereign rating downgrades have a weaker link with the drop of stock returns and Z scores than do active bank rating downgrades. This offers evidence that the active downgrades of bank ratings after sovereign rating downgrades provide extra information to the stock market and the predictability of insolvency risk besides the independent impact of sovereign and bank rating downgrades.

2.4.3 Robustness check

I conduct three robustness tests, two for the short-term analysis and one for the long-term analysis.

For short-term analysis, I replace the time windows of [t-1, t+T] by [t, t+T] to consider the shock of sovereign ratings on the stock returns with the day when the ratings are released as the benchmark day. In the main test, I take the day before the rating change announcement day, (t-1), as the benchmark to rule out possibility that CRAs announce the rating changes after the stock transactions terminate on the announcement day. However, the cost of using [t-1, t+T] instead of [t, t+T] is that I ignore the time interval [t-1, t] and do not consider some possible market events during this interval which may also impact the stock returns. Therefore, I analyze the cases of [t, t+T] and re-run all the regressions shown in Models 2-1-1, 2-1-2 and 2-1-3 to examine the consistency of the results.

To save space I do not show the regression tables in the main part but have put them in Appendix (Appendix 2-2). I do not find significant changes of results from the original tests using time window [t-1, t+T] in terms of the sign, size and significance of coefficients on key independent variables. This shows that the omitted events (if applicable) do not influence the estimation of the impact of sovereign ratings on the stock returns, or the role of sovereign-ceiling policy.

Another robustness check is to apply two-way clustering of standard errors to re-estimate the t-value of estimators. To deal with the possibly existing heteroscedasticity problem (unobserved characteristics of observations are correlated with each other within same clusters, for example, same stock/bank[4], same country or same year), I cluster standard errors for all regressions in Models 2-1-1, 2-1-2 and 2-1-3 by year level and stock/bank-year level (two-way clustering). The two-way clustered standard errors are adjusted by (N-1)/(N-P)× G/(G-1),where N is the sample size, P is the number of independent variables, and G is the number of clusters (Ma, 2014). To save space I do not show the regression tables in the main part but they are put in the Appendix (Appendix 2-3). The re-estimation of t-value does not change the sign or the size, but only the standard error and significance of estimators. I find a significant reduction of t-values for all of the estimates after the re-estimation, but only a few of the estimates turn to be insignificant (having been significant in the original regressions). For details, the D-i-D estimators in Model 2-1-3 (on the interaction term between *At_Ceiling* and $SRD\_Followed\_By\_BRD$) for the time windows of [t-1, t+2] and [t-1, t+6] are significantly positive in the original models but insignificant after I cluster

[4] Stock level for stock return cases and bank level for Z score cases.

the standard errors. The significance of all the other estimators except these two remain even if I use two-way clustering of the standard errors.

For the long-term analysis of Z scores, I take the robustness check of changing the format of Z scores (the dependent variable). As mentioned in the section of 'Data and Sample', I do not take the time-varying ROAA, CAR or $\sigma(\mathrm{ROAA})$ into consideration when establishing the Z score indicator for analysis. In this robustness check, another two formats of Z scores, $Z(Alternative\ 1)_t$ and $Z(Alternative\ 2)_t$, also mentioned by Lepetit and Strobel (2015) are adopted to replace the dependent variables in Models 2-2-1. 2-2-2 and 2-2-3.

$\mathrm{Z(Alternative\ 1)_t} = \frac{\overline{\mathrm{ROAA_{t,3years}}}+\overline{\mathrm{CAR_{t,3years}}}}{\sigma(\mathrm{ROAA})_{\mathrm{t,3years}}}$;

$\mathrm{Z(Alternative\ 2)_t} = \frac{\overline{\mathrm{ROAA_{t,3years}}}+\mathrm{CAR_t}}{\sigma(\mathrm{ROAA})_{\mathrm{t,3years}}}$; where $\overline{X_{t,3years}}$ refers to the three-year moving average of variable X in year t and $\sigma(ROAA)_{y,3years}$ refers to the three-year moving standard deviation of ROAA in year *t*.

The correlations between each pair of the three Z scores are shown in Table 2-9.

Table 2-9 Correlation Matrix among the three proxies of Z scores

	Z (Original)	Z (Alternative 1)	Z (Alternative 2)
Z (Original)	1	0.2489	0.246
Z (Alternative 1)		1	0.9993
Z (Alternative 2)			1

I find that the correlation between $\mathrm{Z(Alternative\ 1)_y}$ and $\mathrm{Z(Alternative\ 2)_y}$is extremely high (99.93%) so these two substitutes can be regarded as the same one. I replace the original Z score with $\mathrm{Z(Alternative\ 1)_y}$ and re-run the regressions in Models 2-1-1, 2-1-2 and 2-1-3. The results of updated regressions are put in the Appendix (Appendix 2-4). I find that the only significant change of empirical results is for Model 2-2-1. The estimates on SRD are significantly negative in the original model, while after I change the format of Z scores, the estimates are still negative but not significant except in the case of S&P. However, estimates on $SRD\_Followed\_By\_BRD$ remain significantly negative. Therefore, although the results of Model 2-2-1 are different for different Z scores, this does not change the conclusion regarding the Hypothesis 2-1: the follow of bank rating downgrades enhances the power of sovereign rating downgrades.

2.5 Conclusion

I empirically examine the role that bank ratings play in the mechanism by which sovereign ratings affect bank performances. Twenty-five main banks from PIIGS countries which received a significant number of sovereign rating downgrades in the sample period (1991-2017) are selected as the research sample. For the sample banks, I identify 504 sovereign rating downgrade events and find that these sovereign rating downgrades have a significant relation with the short-term performances of stock returns of those banks in time windows no more than 10-day. I further select those sovereign downgrade events which are followed by bank rating downgrades within no more than two transaction days, test the association between those specific sovereign events and the stock returns and find a significant relationship with larger magnitudes (larger sizes of estimated coefficients) than those sovereign rating downgrades not followed by bank ratings. To further rule out the effect of following bank rating downgrades, I apply the cases of bank rating downgrades following sovereign rating downgrades which trigger the sovereign-ceiling policy and hence are regarded as 'semi-passive' reactions to sovereign rating downgrades. The semi-passive bank downgrades are associated with a weaker effect on the stock returns than active downgrades, which indicates that the active bank downgrades provide extra information about the negative performances of corresponding banks to the investors as well as the independent effects of the sovereign rating downgrades and the subsequent bank rating downgrades. This finding supports my hypothesis and is consistent with the statement that bank ratings play a role of enhancing the power of sovereign rating's impact on bank performances (i.e. bank ratings partially transmit the effect from sovereign ratings to the bank performances).

I extend my analysis of short-term performances of bank stock returns to a long-term indicator, Z score, which mirrors the insolvency risk of banks on an annual basis. Z score is an indicator of banks' credit risk and the role of CRAs is to assess the credit risks of firms. Therefore, I test the association between Z score in the current year and the rating levels (both sovereign and bank ratings) at the end of the previous year to investigate the information (i.e. predictability of future credit risks) provided by sovereign ratings in two scenarios, 1) SRs are followed by BRs and 2) SRs are not followed by BRs. Parallel tests, similar to those for stock returns, are conducted on the annual dataset of Z score, sovereign rating changes and a series of accounting-based control variables. I find similar empirical results to those for the stock return analysis: sovereign downgrades have a significant link with the decrease of Z score (i.e. the increase of insolvency risk); bank downgrades following those sovereign downgrades enhance such link and provide extra information (predictability) to the Z score variations.

I acknowledge two limitations in my research. The first limitation is that I only consider downgrade cases but not upgrade ones. The reasons for ruling out upgrade scenarios are, 1) the sovereign ceiling policy only works for sovereign and entity rating downgrades and 2) the literature has concluded that investors/firms react to bad news (downgrades) more significantly. However, this reduces the number of sovereign rating changes included in my sample and leaves a gap of the effect of sovereign rating upgrades on the market. The second limitation is the selection of PIIGS but not all the EU countries because other countries received zero or very few sovereign downgrades in the sample period. However, it may also have some negative consequences on the representativeness of my sample.

3. Chapter III ABS market reaction to credit ratings before and after the financial crisis

“The default rates (of AAA tranches) are already up from 1% to 4%, fellas. And if they rise up to 8%, and they will, a lot of these BBBs are going to zero too.”

--Lines in the movie ‘Big Short’ (2016) in a scene when a financial analyst explains the possibility of the ABS market collapsing (including the collapse of highly-rated ABS tranches) to some fund managers before the 2008 global financial crisis

3.1 Introduction

The US subprime mortgage crisis (2007) and the accompanying global financial crisis (2008) highlight the role played by CRAs and the importance of the asset securitization market. CRAs have been criticized for providing structured finance products (mainly represented by ABS, asset-backed securities), securities issued in the asset securitization market, with inaccurate and biased ratings (Morkötter et al, 2009; Griffin et al, 2011; He et al, 2011; Kraft, 2015). These ratings convinced investors to invest in an astonishing amount of ABS (asset-backed securities), particularly MBS (mortgage-backed securities) (Friedman and Posner, 2011).

In this light, this chapter is designed to study the market reaction to ratings provided by CRAs with regard to ABS (including MBS) and the possible change in this reaction in the wake of the financial crisis. The reason for selecting ABS to study CRAs is not only that ABS were the first sector to collapse in the financial crisis but also that the ABS market is believed to have reacted to credit ratings to a greater extent than other types of investors through the following channels: information intermediate function, historical behavioral reliance and rating-based regulations (Fender and Mitchell, 2005; Coval et al., 2009).

The reaction of the ABS market to credit ratings is a natural phenomenon under a condition of information asymmetry. CRAs (mainly the top three, Moody’s, S&P and Fitch) are trusted by market participants due to ‘the financial market complexity and borrower diversity’ (Cantor and Packer, 1995). The information intermediate function is more significant in a structured finance market because of the complexity of ABS securities.

In addition, due to their historical reputation, leading CRAs have ‘trained’ investors in a behavioral pattern of reacting to their ratings. For example, many market participants use credit ratings offered by the top three CRAs as a ‘trigger’ of commercial contracts. Some investors require traders to sell certain securities immediately if they are downgraded below certain boundaries, such as the BBB notch. For the structured finance market, the behavioral reaction to credit ratings still exists because structured finance products were created at least 70 years, after credit rating industry was created so structured finance investors inherited the thinking pattern of reacting to CRAs (Servigny and Jobst, 2007).

Another reason for investors’ reaction to CRAs involves financial regulations. Since the 1970s, the SEC has gradually taken action to link regulatory requirements to ratings. In Basel II, at least two types of regulation, risk-sensitive capital and investment limitation, are based on credit ratings. When calculating capital, financial institutions (particularly banks) are allowed by the policy to use different weights on securities with different credit ratings. Hence, as institutional investors, banks have to react to ratings by adjusting their investment portfolio according to credit ratings given to the securities. Another regulation concerning ratings is investment limitation, whereby certain investors are not allowed to hold securities under certain levels of rating grades (Darbellay, 2013).

However, the three channels mentioned above have undergone some changes since the 2007 subprime crisis. The CRAs’ function as information intermediates has been questioned (Mattarocci, 2013); their reputation has been dramatically undermined (Lynch, 2008) and regulators have expressed their willingness to remove credit ratings from regulatory requirements (Darbellay, 2013).

CRAs failed to foretell the collapse of subprime securities before the crisis occurred. Such poor performances are not consistent with the role of information providers which CRAs should have played. Therefore, they were subject to a large number of harsh comments (Lynch, 2008; Morkötter et al, 2009; Griffin et al, 2011; He et al, 2011; Mattarocci, 2013; Kraft, 2015). It was questioned whether CRAs were able to remove information asymmetry as they are required to do and whether the market may not regard ratings as a source of extra information. Thus, due to the criticism of CRAs' poor performances, market reactions may be weakened.

Regarding regulation changes in the rating industry, the most significant action taken by US regulators was the release of the Dodd-Frank Act 2010. This is a financial market reform plan signed by President Obama aiming to re-regulate the financial system in response to the financial disaster. This Act highlights that credit ratings should be gradually removed from the criteria of financial regulations. Reformers claim that the removal of rating-based regulations can eliminate the influence of credit ratings on the financial system from the regulatory perspective.

In the context, I conduct an empirical test to study the reaction of ABS to credit rating actions before and after the global financial crisis. The main objective of this research is to assess the extent of the market's reaction to ratings and figure out whether this reaction has diminished since the 2008 financial crisis, as many articles suggest (Lynch, 2008; Darbellay, 2013; Mattarocci, 2013) and as the regulators expect.

The research contributes not only to investors and rating agencies themselves, but also to the normal operation of the financial system. On the one hand, the reaction of investors to ratings provides a possibility of realizing information symmetry, which is a vital element of the efficient market theory. However, on the other hand, since conflict of interest exists in the rating market, the impact of ratings on the market may make investors' decisions biased or even harm the financial system.

Conflict of interest results from the issuer-pay business model of CRAs and an oligopolistic trend of the rating industry (high concentration of the Big Three and barriers to new entrants) and the collective market power of the Big Three (Mattarocci, 2013). All these three factors (conflicts of interest, oligopolistic trend and the Big Three CRAs' collective market power) can be enhanced by the fact that the market relies on CRAs. Investors' trust in CRAs makes issuers more willing to maintain the issuer-pay model and pay CRAs for a satisfactory rating to attract investors. Furthermore, the influence of ratings on the market creates a high profit for leading CRAs, exacerbating the concentration in the rating industry and raising the barriers to small and new CRAs. Thus, reactions to CRAs may undermine market efficiency via conflict of interest, while at the same time enhancing conflict of interest.

This chapter is structured as follows. Section 3.2 consists of an introduction to CRAs and ABS, a literature review of related research of other scholars and a list of the contributions of this paper beyond the existing literature. Section 3.3 describes the dataset used and my empirical results as well as robustness test results. In Section 3.4 I present my two main hypotheses and four sub-hypotheses about the market reactions to credit ratings, raise two assumptions to make hypotheses reasonable, and state the methodology used to test these hypotheses for both the primary market data and secondary market data. Section 3.5 concludes the chapter.

3.2 Background, related research and contribution

My research in this chapter can be positioned into three strands of literature: CRAs' market reaction, the ABS (structured finance product) ratings and the evaluation of CRA performances. The first strand of literature uses different measures of market reaction (bond/stock prices, CDS, cross-country effects etc.) to test CRA's influencing power. The second strand of literature discusses the mechanism of the issuance of

ABS and the reaction of ABS prices to rating actions. The third strand consists of positive and negative views on the reform of CRA industry.

My research makes incremental contributions to the three strands of literature: firstly, I use both the issuance- and transaction- period data to measure the market reaction to CRAs' actions. Secondly, I include different types of ABS in my dataset to contribute the second strand of literature. Lastly, by comparing the post-crisis reaction of ABS market to rating actions with the pre-crisis one, I supplement the literature of CRA performance evaluation and find that the reaction is weaker after the financial crisis.

3.2.1 Market reaction to CRAs

In this section, I summarize the literatures which study the relationship between the market reactions and CRAs' actions. The literature can be divided into two streams: theoretical research and empirical research.

Theoretical papers aim to study the economic equilibrium between credit rating providers (CRAs) and market participants. Bolton et al. (2012) establish a game theory model on the equilibrium of the behaviors of CRAs, debt issuers and investors in order to investigate the effect of CRA competition on the rating quality given by the agencies and to investigate the relationship between the trust of investors and the rating quality. Fender and Mitchell (2005) successfully foretell the possibility of model risk of rating agencies due to the over-reliance on ratings. Noh and Dong Woo (2014) build a game theory model with five participants: one issuer, one private credit rating agency, one public credit rating agency, one 'rater' with information acquisition technology and a continuum of investors. They conclude that a reform creating a 'public CRA' can work only if the distribution of type of issuer projects and the impact of high rating benefits are known.

In terms of empirical research on the market (investors') reactions to the credit ratings, early papers focus on the credit ratings of conventional bonds (West, 1973; Weinstein, 1977). Recent papers have tried to find more details about the bond price reactions to credit rating actions. Kliger and Sarig (2000) checked the bond ratings' influence on the firm, debt and equity values and implied options prices. Iannotta et al. (2013) applied the concept of 'quality spread' (the yield difference between the Baa and Aaa tranches) to represent the predictive power of ratings and demonstrated that the influence of credit ratings on the issuance spread is greater if the 'quality spread' is higher. Abad and Robles (2015) tested the historical rating change announcements and their effects on the risk-return binomial, concluding that the CRAs' rating announcements reveal new information to the market.

Other than normal bonds, other types of bonds have also attracted attention in academic studies. Liu and Thakor (1984) investigated the independent impact of ratings on state bond yields, while Stover (1991) focused on the relationship between the yield of newly issued municipal bonds and bond ratings.

In addition, many scholars have discussed the relationship between stock prices and rating announcements. Hand et al. (1992) compared the result of the stock market with that of the bond market and found asymmetric effects between negative and positive announcements, as well as distinct effects on investment-grade securities and non-investment-grade securities. Dichev and Piotroski (2001) tested the long-run variation of stock returns following corresponding bond rating changes. Jung et al. (2013) examined how credit ratings affect the behavior of stock analysts' earnings forecast revision. An interesting research conducted by Agarwal et al. (2016) uses text-mining techniques finding a significant relationship between the tones of the texts in rating action reports and the CAR (cumulative abnormal return) in the secondary market. This finding strengthens the hypothesis of the CRAs' influence on the financial market.

Apart from traditional financial instruments, bonds and stocks, related derivatives such as CDS (credit default swap) are of interest to many scholars (Hull et al., 2004; Chava et al., 2012; Drago and Gallo, 2016). The empirical literature also covers the impact of credit ratings on activities in the financial market, such as payment methods in the M&A process (Karampatsas et al., 2014), capital structure decisions (Kisgen, 2006), sovereign issuance funding (Kiff et al., 2012) and real private investment (Chen et al., 2013). Moreover, other studies (Kräussl, 2005; Afonso et al., 2012) discuss the impact of sovereign rating announcements on countries' indicators of macroeconomic condition, reflected by an established index of speculative market pressure and sovereign bond/CDS prices.

To investigate the market reaction to credit ratings, scholars do not only use the data within single countries but also study the cross-country effect from the rating actions in one country to the financial market of another country. Ferreira and Gama (2007) use a dataset including 29 countries and find that the rating actions for the sovereign debt in one country have an effect on the stock market in other countries. Grammatikos & Vermeulen (2012) extend this investigation by studying the contagion effect between different country groups. Besides the stock market, cross-country effects on exchange rate market are also discussed. Subaşı (2008) use emerging market data to study whether the upgrades/downgrades of a sovereign rating would have an impact on the exchange rate in other countries. Alsakka, R., & ap Gwilym, O. (2012, b) further test whether three main CRAs have different patterns of the impact on exchange market.

3.2.2 Credit ratings of structured finance products

This paper focuses on the credit ratings of structured finance products. Structured finance (Asset-Backed Security, known as ABS) is an important outcome of financial innovation in the 20th century. In contrast to traditional investment instruments through which the issuers and investors of the securities transact directly, in ABS transactions, an institution called a Special Purpose Vehicle (SPV) organizes the transactions as a bridge between the specific issuer and the general investors. The investors receive the payments in an order based on their payment priority, reflecting the purchasing prices or spread (this procedure is called 'tranching' and each of the payment obligations with specific payment priority is called a 'tranche').

The process described above is also called asset securitization. The incentives driving the creation and evolution of asset securitization were summarized by Cowan (2003), who points out that traditional mortgages were illiquid for investors, exposing lenders to the risk that they may not be able to find buyers when they wished to sell the securities they hold.

Credit ratings are essential to asset securitization, because according to the regulation, simultaneous to issuing the tranches of an ABS, issuers need to turn to the CRAs asking them to give each of the tranches a 'rating', demonstrating its default risk. Due to the complexity of ABS stemming from the pooling and tranching procedures, investors tend to believe the opinions offered by the CRAs via their rating results on the securities.

Some studies indicate the reaction of the ABS market to credit ratings by testing the association between ABS issuance spread and its credit ratings holding other variables constant. Ashcraft et al. (2011) investigated the relationship between the rating given by CRAs and the prices of MBS and found that rating and yields were always correlated: higher rating, lower yields. Similarly, Fabozzi and Vink (2012) tested European ABS data to assess the significance of the ratings' parameters on the yield spread (focusing only on the AAA tranches, which attract the most attention from the market).

In contrast to the papers above where the authors directly regress issuance spread on the ratings, other scholars use alternative factors to indicate ratings' influences. Mählmann (2012) used the CDO-ABS issuance yield's ability to predict the future outcomes.

3.2.3 Evaluation of CRA performances

Researching on the bond rating industry (not the ABS or CDO), Baghai et al. (2014) get a conclusion that the CRAs were getting more and more conservative in rating corporate debts since 1985 instead of inflating the ratings which means that for same PD, they gave lower ratings. Other scholars test the bond market data (bond spreads) to demonstrate the conflicts of interests of CRAs (Covitz et al., 2003). For the securitization products (CDO), some papers also conduct research on the credit rating agencies and give them positive remarks. Griffin, et al. (2013) distinguish the concept of rating shopping, where investors solicit the 'best' rating among the multiple agencies and that of rating catering, the CRA's incentives to attract businesses. Peña et al. (2015) use the Italian market data to reject the hypotheses of rating catering

Although a large number of scholars defend the credit rating agencies by empirical tests, some other authors use empirical results to offer negative remarks against CRAs. Among those negative papers, most of them claim that they find a clue to prove that CRAs 'inflate' their ratings in order to please the issuers who pay the rating fees. He et al. (2011) separate the sample MBS tranches into two parts according to the sizes of tranche issuers (big issuer and small issuer), select an index, the fraction of AAA tranches among all the tranches to demonstrate the 'favour' of CRAs to the issuers. Besides, they use the tranches' price changes during the crisis as a proxy of performances during the crisis and compare the performances of MBS issued by big and small issuers both in the non-boom period (2000 to 2003) and boom period (2003 to 2006). They conclude that CRAs prefer offering 'fake' ratings to big issuers for revenues. Other indicators of rating shopping (or catering) are established to test the performances of CRAs. For instance, Morkötter et al. (2009) define and identify the rating shopping by comparing the characteristics of rated securities. In their story, if the credit rating agencies act in a way of rating shopping, the patterns in the characteristics of CDOs rated by the same credit rating agency should be common and such patterns should be diversified among different credit rating agencies. Their test results demonstrate that there exists a common characteristic pattern within each of the group thus enhance the view of rating shopping. Efing et al. (2013) introduce an index named 'Deal rating-implied spread' reflecting the overall market value of all securities within one deal and empirically identify an association between the issuers' business to the CRA and the ratings offered by the CRA. Such association is stronger for deals with more complicated deal structure. It enhances the statement that CRAs favour 'bigger' issuers and offer bias ratings.

3.2.4 Contribution of this research

In contrast to the majority of researchers who focus on the reaction of traditional financial products (bonds and stocks) to credit ratings (West, 1973; Weinstein, 1973; Liu and Thakor, 1984; Stover, 1991; Hand et al., 1992; Kliger and Sarig, 2000; Dichev and Piotroski, 2001; Iannotta et al., 2013; Abad and Robles, 2015). Those research finds a significant association between the credit rating levels (changes) and the market prices (or variation of market prices). Among these scholars, only a very small group of researchers have studied structured finance products (Ashcraft et al., 2011; Fabozzi and Vink, 2012) and find a relationship between spreads and credit rating levels. Even among that limited number of papers concerning structured finance market ratings, almost all discuss mortgage-backed securities while omitting other types of ABS in their datasets. My research includes not only MBS but also other non-MBS to reflect the entire structured finance market.

Furthermore, previous research focuses on the pre-crisis situation (Hand et al., 1992; Kliger and Sarig, 2000; Dichev and Piotroski, 2001) while my study aims to compare the situations pre- and post- to investigate whether the market reaction to changes in ratings has become weaker after the financial crisis. The reason for differentiating between pre-crisis and post-crisis performances of the credit rating impact on the ABS market is that the recent financial crisis has undermined CRAs' reputation by a considerable number of media reports making negative comments on the CRAs' role in the crisis. Whether such great reputational loss has led to a decrease in the ABS market reaction to credit ratings has not been studied previously, to my knowledge. Furthermore, US credit rating reforms which were declared after the crisis aim to remove the rating-based regulations so it provides a background that investors may react to those ratings to a lower extent than they did in the pre-crisis era.

Although research on the traditional bond or stock markets uses data of the secondary market (Hand et al., 1992; Dichev and Piotroski, 2001), most of the previous research on structured finance products investigates only the primary market data, which covers the security issuance stage but not the transaction stage (Fabozzi and Vink, 2012). This leaves a gap in the research on the reaction of ABS spread/prices to credit ratings. As mentioned in Section 3.1, three bridges between investors and CRAs are the information intermediate function of CRAs, rating-based regulations, and investors' behavior. The primary market's reaction to CRAs can partially reflect CRAs' function of information intermediates as investors indirectly capture non-public information on issued ABS by observing ratings. The reaction also reflects CRA's function as providers of rating-based regulatory license (some regulations about ABS are based on their initial ratings). The secondary market's reaction is a reflection of the function of information intermediates (investors view downgrades as a negative signal) and regulatory license providers (some market participants are required by regulations to sell certain securities if they are downgraded). It also reflects the behaviors of investors (for instance, homogeneous selling following a downgrade) due to the feature of real-time trading in the secondary market. Therefore, as an essential part of the asset securitization market, the transaction stage of structured finance products should not be ignored. In this paper, to comprehensively study the ABS market, I investigate both the primary and the secondary ABS markets. The cross-sectional and the panel data analyses are conducted to demonstrate the market reactions to ratings in those two markets, respectively.

3.3 Hypotheses, assumptions and methodology

3.3.1 Hypotheses and assumptions

I split my empirical test into two parts: issuance data for the primary market and transaction data for the secondary market.

Two hypotheses are proposed to test the reaction of the ABS market to credit ratings and the potential change in this reaction after the financial crisis.

Hypothesis 3-1: There exists a significant association between security prices and the issuance/change of credit ratings in the ABS market.

Hypothesis 3-2: The association between security prices and the issuance/change of credit ratings in the ABS market has become significantly weaker after the financial crisis.

For Hypothesis 3-1, two sub-hypotheses are designed to reflect the situations in the primary market and the secondary market, respectively.

Hypothesis 3-1a: In the issuance stage of ABS, controlling for a set of characteristics variables, the ABS issuance spread is significantly associated with their issuance credit ratings.

For issuance data, the market reactions to credit ratings are reflected by the association between the variation of issuance credit ratings among different ABS tranches and the variation of issuance spread of those ABS tranches after controlling identified risk characteristics of the tranches. Issuance spread is defined as the formula

$$Issuance_{Price} = \sum_{t=1}^{T} \frac{Cash\_Flow_t}{[1 + (benchmark\ rate + spread)]^t}$$

In the issuance stage, ABSs are priced relative to a benchmark interest rate in a form of 'yield'. Issuance spread is the part of issuance yield above the benchmark rate. A higher issuance spread is equivalent to a lower issuance price. Fabozzi et al. (2012) state that the issuance credit ratings mirror information of ABSs' risk characteristics and that those characteristics are open to ABS investors in the ABS issuance reports. Therefore, if the issuance ratings still affect the issuance spread controlling all of the characteristics equally, it is reasonable to claim that investors consider extra information besides open information when they price newly-issued ABS.

Hypothesis 3-1b: In the transaction stage of ABS, a significant price decrease occurs in certain time windows after one ABS receives negative rating announcements from CRAs.

For transaction data, the market reaction to credit ratings can be evaluated through the price reactions to rating change announcements. When an ABS receives negative credit rating announcements from CRAs, investors react to them by accepting lower transaction prices, which is reflected by a significant price decrease in certain windows after the announcements are released.

In my research, 'rating change announcements' are identified as four types of announcements offered by CRAs about certain ABS (shown in Table 3-1):

Table 3-1 Four types of rating announcements

	Real rating change	Possible rating change[5]
Positive	Actual upgrade	Possible upgrade
Negative	Actual downgrade	Possible downgrade

[5] put into watch lists or outlook announcements

According to many studies (Hand et al., 1992; Dichev and Piotroski, 2001; Jung et al., 2013; Drago and Gallo, 2016), shocks of positive announcements on the market are weaker than those of negative announcements. In my research about ABS' price reactions, I also find consistent evidence of such asymmetric shocks. Therefore, in this paper I use only negative announcements (actual downgrade and possible downgrade) as the testing sample. 'Actual downgrade' refers to an announcement indicating that the CRA has decided to downgrade the ratings of certain ABS while a 'possible downgrade' announcement is just a warning that the CRA may downgrade that ABS at a certain time in the future.

Hypothesis 3-1b implies that the immediate price reactions to negative rating announcements can be a proxy of investors' attitudes towards those announcements. If I can find evidence to show that, compared to non-announcement dates and controlling for relevant variables, more negative price returns are observed on days in a certain window around negative rating announcements, it may indicate that investors follow the CRAs' downgrade suggestions by accepting a lower transaction price of that downgraded ABS.

Similar to Hypothesis 3-1, I also divide Hypothesis 3-2, which indicates a decreased reaction to ratings, into two sub-hypotheses according to the market division:

Hypothesis 3-2a: Compared to the pre-crisis period, the association between ABS issuance spread and issuance ratings has become weaker since the financial crisis.

Hypothesis 3-2b: Compared to the pre-crisis period, the size of ABS transaction price decrease following negative credit rating announcements has diminished after the financial crisis.

Each sub-hypothesis works for each market (primary or secondary), indicating a lower degree of market reaction to CRAs' actions.

I realize that the rating market and ABS market have both experienced a profound change since the financial crisis and that therefore some factors may make my hypotheses invalid: 1) if, in the primary market, CRAs systematically adjusted their implications of rating scales which differentiates the meaning of same rating scale after the crisis, then the ratings in two periods are incomparable thus the seemingly weaker association between ratings and issuance spreads are not attributed to a weaker market reaction but to the rating-scale implication transformation; 2) if, in the secondary market, the transaction liquidity has been significantly reduced since the financial crisis which makes the market inactive, then the seemingly weaker association between price variation and rating announcements is not a reflection of weaker market reactions to ratings but that of an inactive market.

Therefore, in order to ensure that my hypotheses are valid, two assumptions are raised and tested:

1) The implication of issuance rating scales at a same level does not show a significant change after the financial crisis;

2) The liquidity of the secondary ABS market is sufficiently high to maintain the market active in the post-crisis period.

3.3.2 Methodology

I conduct analyses on the primary and the secondary market situations to test my hypotheses. For the tests of each market, corresponding assumptions are firstly tested before regressions of (issuance or transaction) price indicators on rating indicators are conducted.

3.3.2.1 Primary market (Hypotheses 3-1a and 3-2a)

Assumption: rating implication stability

The assumption of the main test concerns the stability of rating scales before and after the financial crisis. In other words, I need to check whether rating agencies imply different risk characteristics by the same rating levels after the financial crisis and to confirm that rating scales before and after the financial crisis are comparable, which is an essential condition of my main test.

I follow the research by Fabozzi and Vink (2012) who test the determination of rating scales by running ordered logit regressions of issuance rating indicators on a series of fundamental characteristics. To check whether rating agencies have significantly adjusted such determination after the financial crisis, I add a dummy (equal to 1 if the ABS is issued after the financial crisis) as an independent variable to estimate the degree of rating-implication drift in the post-crisis period.

The dataset is divided into two sub-samples: MBS and non-MBS. MBS is a special type of ABS whose backing securities are mortgage-related. The reason for separating MBS from other ABS is that the spread determining regime, the risk characteristics, and the credit rating features differ between mortgage-backed securities and other types of ABSs. All of the research on the primary market is conducted separately for MBS and non-MBS datasets.

The assumption test is conducted separately for each rating agency of the big three (Moody's, S&P and Fitch).

I have put the regression results in the Appendix (Appendix 3-2). My results show that the estimated coefficients on the post-crisis dummy are insignificant, which shows that controlling fundamental characteristics, rating agencies do not over-rate or under-rate ABS after the financial crisis. This enhances my assumption that the rating implications of the same rating levels are stable in the two periods thus the ratings offered by rating agencies are comparable before and after the financial crisis.

Main Test

OLS regression analyses were designed to test the association between the issuance spread of ABS and the rating-related variables, the time dummy variables and the interaction terms of those two types of variables, viewing the tranche characteristics as control variables.

My main regressions are displayed in Equations (3-1) and (3-2).

$$\ln(spread_i) = \alpha_{3-1} + \beta_{3-1,1}NR_i + \beta_{3-1,2}N_i + \sum_{p=1}^{P} \beta_{3-1,(p+2)}C_{pi} + \varepsilon_{1,i} \qquad (3-1)$$

$$\ln(spread_i) = \alpha_{3-2} + \beta_{3-2,1}NR_i + \beta_{3-2,2}N_i + \beta_{3-2,3}DC_i + \beta_{3-2,4}PC_i + \beta_{3-2,5}NR_i \times DC_i + \beta_{3-2,6}NR_i \times PC_i + \sum_{p=1}^{P} \beta_{3-2,(p+6)}C_{pi} + \varepsilon_{2,i} \qquad (3-2)$$

A description of all the variables is given in Table 3-2 (the details of variable NR_i are shown in Table 3-3) and C_{pi}s refer to the nine variables of tranche characteristics playing the role of control variables in this regression. Some of the control variables are introduced in Fabozzi's paper (2012) and the rating-related and dummy-related variables are introduced in this paper in order to test Hypotheses 3-1a and 3-2a. A trade-off between the size of the sample and the diversity of control variables has to be considered in this analysis. Since not all information on tranches on all control variables can be collected, adding some of the control variables (WAL, WAC and credit support) reduces the size of the samples used to estimate the coefficients. Therefore, I cluster the control variables into three levels (shown in Table 3-2). Variables of Level 1 indicate basic information of the ABS tranches and are available for the full sample. Variables of Level 2 (WAL and WAC) consider the factors of length, the coupon rate of the whole ABS deal and are available for a sub-sample of the full sample. The variable of Level 3 indicates the risk protection offered by the issuers to the specific tranches. Regressions are run separately controlling different levels of variables (equivalent to different values of p shown in Equation (3-2)) and the consistency of results is tested among the three levels of control variables.

Table 3-2 Description of variables in the issuance dataset

Category		Variable	Notation in Equations (3-1) and (3-2)	Description
Dependent Variable		Ln(Spread)	Ln(Spread)	The logarithm of yield of the Asset-backed security (MBS or non-MBS) relative to the benchmark yield. Spread is negatively correlated to the issuance price. A higher spread is equivalent to a lower price.
Control Variables	Level 1	Par amount	C_1	The size of the tranche
		CPN	C_2	The coupon rate set before issuance
		Tranche number	C_3	The seniority number of the tranche in the whole deal: a smaller number indicates a higher seniority which means a higher priority to claim the interest/principal payment among all of the tranches in the deal.
		Length	C_4	The pre-determined life of the security, the length between the maturity date and issuance date.
		Issuer's size	C_5	Ratio of the sum of ABS issuance volume issued by the issuer to the sum of ABS issuance volume issued by all the issuers in the whole dataset. This index indicates the market share of the ABS issuer: a higher value means a larger market share.
		Collateral type	C_6	A series of dummy variables indicating the type of assets backing the Asset-backed security. For MBS, key types of assets include 'commercial mortgage', 'residential mortgage' and 'wholesale mortgage'; for non-MBS, key types of assets include 'CDO', 'CLO', 'student loans', 'auto loan receivables', 'credit card receivables' etc.
	Level 2	WAL	C_7	Weighted average life
		WAC	C_8	Weighted average coupon rate
	Level 3	Credit support	C_9	Original credit support percentage for an ABS class/tranche from other subordinate classes in the same ABS deal.
	Region	Country	C_{10}	A series of dummy variables indicating the country where the security was issued. The codes used are: KY-Cayman Islands US-United States GB-Great Britain AU-Australia NL-Netherlands IE-Ireland
Credit-rating variables		Number of CRAs rating the security	N	It indicates how many CRAs among the Moody's, Standard & Pools, Fitch and DBRS offer ratings to the tranche. This variable indicates the rating-industry competition related to the ABS.
		Number-format Average rating	NR	Transform the letter-format rating to number-format based on a formula shown in Table 3-3. Calculate the average rating of all the ratings the security receive.
Period dummy variables		During-crisis dummy	DC	Equal to 1 if the tranche was issued during the financial crisis period (Sep.1st, 2007-Dec.31st, 2009), to 0 otherwise.
		Post-crisis dummy	PC	Equal to 1 if the tranche was issued after the financial crisis period (after Dec.31st, 2009), to 0 otherwise.

Table 3-1 Transformation between the actual rating notches and number-format variables (NR)

Rating notch (Moody's)	Rating notch (S&P and Fitch)	Value of number-format variable in Equations (1) and (2)	Letter-format dummy variable in Equations (3) and (4)
Aaa	AAA	1	N/A (Benchmark notch)
Aa1	AA+	2	LR_1
Aa2	AA	3	LR_2
Aa3	AA-	4	LR_3
A1	A+	5	LR_4
A2	A	6	LR_5
A3	A-	7	LR_6
Baa1	BBB+	8	LR_7
Baa2	BBB	9	LR_8
Baa3	BBB-	10	LR_9
Ba1	BB+	11	LR_{10}
Ba2	BB	12	LR_{11}
Ba3	BB-	13	LR_{12}
B1	B+	14	LR_{13}
B2	B	15	LR_{14}
B3	B-	16	LR_{15}
Caa1	CCC+	17	LR_{16}
Caa2	CCC	18	LR_{17}
Caa3	CCC-	19	LR_{18}
Ca	CC	20	LR_{19}

Equation (3-1) is linked to Hypothesis 3-1a: $\beta_{3-1,1}$ indicates the association between ratings and the issuance spread: a significant positive $\beta_1$supports Hypothesis 3-1a by showing a positive association between a lower rating (equal to a higher NR_i) and a lower price (equal to a higher $\ln(spread_i)$) when controlling for all of the ABS characteristics. This implies that even when investors see the open information on ABS characteristics, they still offer lower prices to purchase an ABS if CRAs rate that ABS at a lower rating degree.

$\beta_{3-1,2}$ is related to the competition among the different CRAs on the issuance spread. Becker and Milbourn (2008 and 2011) and Dittrich (2007) discuss the relationship between rating-industry competition and rating quality as well as issuer preference. Moreover, regulators are trying to enhance the competition of the rating industry (the

US Credit Rating Agency Reform Act 2006 and EU CRA Regulation 2009). Therefore, I add competition-related independent variables to control the effects of intra-industry competition on issuers' attitudes.

Equation (3-2) is designed for hypothesis 3-2a: $\beta_{3-2,1}$ and $\beta_{3-2,2}$ indicate same items as $\beta_{3-1,1}$ and $\beta_{3-1,2}$in Equation (1). $\beta_{3-2,3}$ and $\beta_{3-2,4}$ indicate the change of issuance spread during and after the financial crisis compared to the pre-crisis period, $\beta_{3-2,5}$ and $\beta_{3-2,6}$ indicate the change of the association between ratings and issuance prices during and after the financial crisis compared to pre-crisis period. A negative $\beta_{3-2,6}$ enhances hypothesis 3-2a by indicating a lower $\beta_{3-2,1}$ after the financial crisis than before. A negative $\beta_{3-2,6}$ means that such an association becomes weaker after the crisis.

3.3.2.2 Secondary market (Hypotheses 3-1b and 3-2b)

Assumption: liquidity

The pre-assumption for secondary market tests is that the liquidity is not extremely low, as this may impact the degree of activity of market prices of ABS.

To identify the market liquidity, I use a commonly-used method to calculate the proportional bid-offer spread (Glosten & Milgrom, 1985; Huberman & Halka, 2011; Cui et al.,2018):

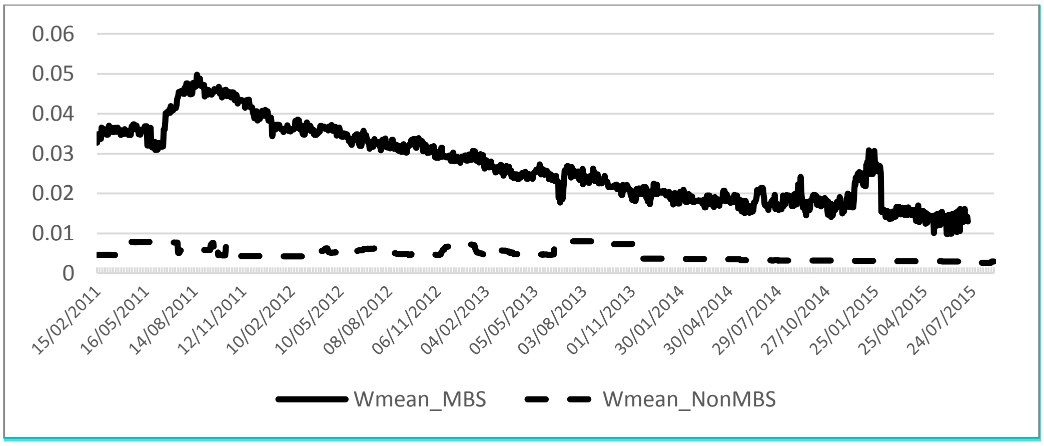
$$s = \frac{\text{Offer Price} - \text{Bid Price}}{\text{Mid\_market Price}},$$

where *Mid-market price* is the halfway (average) between the bid and the offer price. A higher value of *s* implies a lower degree of liquidity.

Due to the limited accessibility of data, I only obtain bid and offer price information starting at March 2011. Therefore, the liquidity levels of the ABS market in the pre-crisis period cannot be estimated. I am able to only find previous papers which describe the post-crisis liquidity of ABS market (Friewald et al., 2015; Friewald et al., 2017). Therefore, I have to ignore the pre-crisis ABS liquidity and only test the post-crisis period.

I collect the daily offer and bid prices of 90 ABS securities (40 MBS and 50 non-MBS) in the time period between 11/02/2011 and 01/09/2015, calculate the proportional bid-offer spreads, take the weighted average of all MBS and non-MBS securities (weighted by asset volume of the ABS), and draw a figure showing the daily variation of the weighted means (shown in Figure 3-1).

Figure 3-1 Daily weighted mean (Wmean) of proportional bid-ask spreads for ABS (MBS and Non-MBS)



Two conclusions can be drawn for the assumption test:

1) Non-MBS has a higher liquidity level than MBS. This may reflect a shortage of the MBS market after the financial crisis due to the collapse of the US mortgage market starting in 2007. However, the proportional bid-ask spreads of MBS have decreased (an increased level of liquidity) since the beginning of my testing window (2011), which can be viewed as a recovery process of the MBS market liquidity.

2) In terms of the absolute levels of the proportional bid-ask spreads, neither types of ABS have extremely low liquidity: even for MBS which has relatively low liquidity, the values of spreads are never higher than 5% and non-MBS spreads are never higher than 1%. However, it is not easy to determine a strict threshold of bid-offer spread to judge whether the liquidity reflected by a spread less than 5% is acceptable

or not. Therefore, the main shortcoming of this test is that I cannot give a clear judgement whether the market is liquid or not.

Main test

In contrast to an issuance dataset which contains static cross-section data, a transaction dataset is a panel one consisting of several security IDs, each of which has a daily time series of transaction prices. To test the price shock of negative rating announcements on transaction prices of ABS, as well as the change of shock degree after the financial crisis, I use fixed-effect panel data regressions, regressing price returns on event-dummy, post-crisis dummy and their interactions.

$$return_{i,t} = \alpha_{3-3,i} + \beta_{3-3,1} \times dE_{i,t} + u_{3-3,i,t} \qquad (3-3)$$

$$return_{i,t} = \alpha_{3-4,i} + \beta_{3-4,1} \times dE_{i,t} + \beta_{3-4,2} \times dP_{i,t} + \delta_{3-4} \times \left(dP_{i,t} \times dE_{i,t}\right) + u_{3-4,i,t} \quad (3-4)$$

The dependent variable, $return_{i,t}$ refers to the price return of the ABS security *i* at time *t*[6]. $dE_{i,t}$ is the event-dummy which is equal to 1 if day *t* is within the pre-defined time windows[7] (1 day, 3 days or 5 days) after a negative rating event occurs. $dP_{i,t}$ is the period dummy which is equal to 1 if the day *t* is in the post-crisis period (after Sep 15th, 2007) and 0 otherwise. $dP_{i,t} \times dE_{i,t}$ is the interaction term, α_i refers to the unobserved time-invariant individual effect and $u_{i,t}$ represents the error term.

I control rating levels of ABS in Equations (3-3) and (3-4) to rule out the possibility that a downgrade of the same number of tranches has a different impact when the initial

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[6] $return_{i,t}=\frac{p_{i,t}-p_{i,t-1}}{p_{i,t-1}}$, $p_{i,t}$ is the reported price of security *i* at day *t* and $p_{i,t-1}$ is the reported price of security *i* at one day before *t*.

[7] Testing time windows are equal to 1, 3 or 5 respectively.

(-n,0): returns in the corresponding columns are calculated as the price difference between the EXACT day of announcement and the average of n days BEFORE the rating event;

(0,+n): returns in the corresponding columns are calculated as the price difference between the average of n days AFTER the rating events and the EXACT day of announcement;

(-n, +n): returns in the corresponding columns are calculated as the price difference between the average of n days AFTER the rating event and the average of n days BEFORE the rating event;

The t-test is for returns of all negative/positive events in each time window.

ratings are different. In addition, year-fixed-effects are also controlled to consider different market conditions in different years.

To enhance the results, I cluster standard errors by three levels respectively, security level, year level and security-year level (two-way clustering). The two-way clustered standard errors are adjusted according to the technique provided by Ma (2014).

Equation (3-3) tests Hypothesis 3-1b by testing whether the returns react negatively to negative rating announcements. A significantly negative $\beta_{3-3,1}$ would support Hypothesis 3-1b by showing that compared with normal days without rating announcements, prices of ABS significantly decrease within a certain window after the release of negative rating announcements.

Equation (3-4) tests hypothesis 3-2b by checking whether estimated $\hat{\delta}_{3-4}$ is significantly positive. The estimator δ can be interpreted as Equation (3-5).

$$\hat{\delta}_{3-4} = \left(\overline{return_{1,1}} - \overline{return_{1,2}}\right) - \left(\overline{return_{2,1}} - \overline{return_{2,2}}\right) \qquad (3-5),$$

where $\overline{return_{1,1}}$=Average return within the pre-defined time windows after a rating event (for the post-crisis period); $\overline{return_{1,2}}$=Average return beyond the pre-defined time windows after a rating event (for the post-crisis period); $\overline{return_{2,1}}$=Average return within the pre-defined time windows after a rating event (for the pre-crisis period) and $\overline{return_{2,2}}$=Average return beyond the pre-defined time windows after a rating event (for the pre-crisis period).

The first item in brackets refers to the rating events' shock after the crisis. The second item in brackets refers to the rating events' shock before the crisis. Therefore, $\hat{\delta}_{3-4}$ is an estimate of the difference between those two shocks, indicating the change of the shock of the events on market returns after the crisis compared with the pre-crisis period. As I state in Equation (3-3), negative rating announcements are associated with negative price returns; a positive $\hat{\delta}_{3-4}$ then would imply a negative price decrease but with a smaller size after the financial crisis, supporting hypothesis 3-2b.

Survivorship bias[8] is a non-negligible factor that may invalidate the results of empirical tests for panel data (Elton et al., 1996). In the context of my analysis, potential survivorship bias is due to the expiration of some ABS before the financial crisis. Those expired ABS did not perform after the financial crisis so I cannot observe or take into account their price reactions to negative rating announcements in my tests. However, I assume that the expiration of ABS does not cause survivorship bias because their maturity is independent of both the financial crisis and the price reactions to negative rating announcements.

For all the 72 ABS analyzed, 22 expired before the financial crisis (before September 2007); all of these ended due to natural expiration based on ABS contracts and not default. Furthermore, all 22 ABS were issued before the financial crisis (from October 1992 to June 2003). According to the contracts, maturities were all determined when the ABS were issued. Thus, the expiration dates were determined before the financial crisis and are therefore independent of the financial crisis. In addition, since the issuers could not 'foresee' the occurrence of negative rating announcements about their ABS and take that into account when they set expiration dates at the issuance stage, the expiration dates are independent with the rating announcements. Therefore, I assume a random expiration of the ABS regarding the financial crisis and rating announcements. Random expirations do not cause survivorship bias because if the expirations are not related to the financial crisis or rating downgrades then it is reasonable to state that if those expired ABS had not expired before the financial crisis, their performances following the credit downgrades would not have been significantly different from other ABS. Thus, I assume that there is no survivorship bias in my study.

[8] Survivorship bias refers to the bias caused by only selecting items which have survived in analysis and neglecting 'dead' ones whose performances are not observed.

3.4 Data

I conduct my empirical analysis using ABS data for issuance stage and transaction stage.

The issuance dataset is collected from the Bloomberg database and Moody's website. Firstly, I go to the Moody's website (https://www.moodys.com/) to download all the issuance reports for newly-issued ABS. By looking up the reports manually, I record the titles and issuance dates for each of the rated ABS. Next, I manually match the titles of ABS with the Bloomberg IDs using Bloomberg database. Lastly, I use the Bloomberg IDs to collect information on ABSs' fundamentals, risk characteristics and issuance ratings given by other main CRAs (Standard & Poors, Fitch and DBRS). Data from these sources are merged into a unique sample containing variables shown in Table 3-2. All of the tranches in this dataset were issued in the period between August 2002 and January 2015 and only the floating-rate tranches are included in the dataset as I do not have access to the benchmark used to estimate the fixed-rate tranches (Fabozzi and Vink, 2012). A total of 24,458 tranches (7,381 MBS tranches and 17,077 non-MBS tranches) from 5,702 ABS deals[9] (1,484 MBS deals and 4,218 non-MBS deals) are in my sample. I separate the MBS from the non-MBS and conduct every analysis in both the MBS data and the non-MBS data respectively.

Regarding the distribution of tranche/deal numbers in three periods[10], two features can be observed here, 1) there are more pre-crisis issued tranches/deals than during-crisis and post-crisis ones; 2) there are significantly more non-MBS tranches/deals than MBS ones.

I calculate the descriptive statistics of all the variables in three periods respectively and describe some pertinent details (Tables are shown in the Appendix 3-1). The

[9] There are a couple of tranches in each of the deals. For each tranche, a seniority number is set to indicate the payment collecting sequence. The regression analysis is conducted on the tranche basis (not on a deal basis).

[10] Details are available upon requests.

explained variable, issuance spread significantly increases after the financial crisis from 4.15% to 5.31% for non-MBS and from 3.88% to 5.05% for MBS (equivalent to a price decrease) but the average ratings of those securities issued after the crisis are even more positive than in the pre-crisis period (indicated by a fall in NR (Number-format Average rating) from 3.72 to 2.73 for non-MBS and from 4.24 to 3.10 for MBS). This phenomenon seems contradictory: the issuance prices do not recover to pre-crisis level when the market recovers although the rating levels recover at the same time. However, if I return to my topic, investors' reaction to the credit ratings before and after the financial crisis, this seemingly 'contradictory' phenomenon should be interpreted as preliminary evidence for the statement that market reaction to issuance ratings of ABS (including MBS) is weaker after the financial crisis. Even if the CRAs convey their confidence in the quality of ABS during the recovery period, the issuance prices remain at a low level, which indicates that the issuers do not accept the positive signal from the CRAs.

The transaction price dataset is collected from Thomson Reuters Datastream and the information on rating changes/levels is hand-collected from Moody's website. I merge data from these two sources into a unique sample.

The sample covers time series between Feb 2001 and Feb 2016[11] (daily) and 72 ABS securities[12]. During this period, 894 rating events on these securities are identified. Due to the

[11] The reason for selecting Feb 2001 as the starting point is to balance the time periods before and after the crisis (around seven years before the crisis, 2001-2007 and seven years after the crisis, 2009-2016).

[12] It is obvious that the number of ABS deals involved in the transaction dataset is much smaller than those involved in issuance dataset. The reason is that compared to all the ABS rated by CRAs in the issuance stage, far fewer ABS receive at least one rating change announcement during the transaction stage. To test the price reaction of ABS to rating events, I only focus on those ABS with rating changes in the testing time period. That is why the number of ABS in the testing sample drops significantly in the transaction-period analysis.

fact that rating events in the secondary market are relatively rare compared to rating offering actions for the primary market, the number of rating events and the tranches involved in these events is smaller than the issuance dataset. Therefore, MBS and non-MBS are analyzed together in this part of the study.

3.5 Empirical results and robustness tests

In this section, I display the empirical results and robustness test results for the primary and the secondary markets.

3.5.1 Empirical results

3.5.5.1 Issuance dataset

For each equation, (3-1) and (3-2), I run two regressions on the MBS sample and the non-MBS sample respectively. The regression results are shown in Table 3-4. The regressions designed for Equation (3-1) (see Columns A and C in Table 3-4) generate a result enhancing Hypothesis 3-1a by showing significantly positive estimations on the variable NR ($\beta_{1,1}$ in Equation (3-1) and the results are consistent regardless of which combination of control variables are taken into consideration). The figures (considering all the control variables) are 0.07 for non-MBS and 0.17 for MBS dataset. They can be interpreted in the following way: after I keep the other risk characteristics constant, if the average rating given by CRAs goes down by one notch (for example, from Ba3 to Ba2), the issuance spread increases by 18.5% (7.3%)[13] for (non-) MBS dataset, which is equivalent to a drop in the issuance prices. This shows that, regardless of the observed information collected from ABS issuance report, investors 'follow' CRAs by demanding a lower purchasing price after seeing a lower rating notch provided by CRAs.

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[13] The figures of the spread's increase are calculated from the estimated coefficients β_1 following the equation: Spread increase proportion=exp(β_1)-1

For the results of Equation (3-2), a positive $\beta_{3-2,4}$ implies that ABS spreads significantly increase after the financial crisis (meaning a lower price). This can be attributed either to a negative trend of the ABS market after the crisis or a higher risk-adverse of investors who require higher returns (spreads) for an ABS tranche with same characteristics in the post-crisis period.

The negative $\beta_{3-2,6}$ enhances Hypothesis 3-2a which shows a weaker market reaction to credit ratings in the primary market after the financial crisis. The figures (controlling all the control variables) are -0.14 for both the non-MBS dataset and the MBS dataset. They can be interpreted as follows: for the (non-) MBS dataset, before the financial crisis, $\beta_{3-2,1}$ is 0.19 (0.17) and after the financial crisis, that coefficient decreases to $\beta_{3-2,1}$+$\beta_{3-2,6}$=0.19-0.14=0.05 (0.17-0.14=0.03). Equivalently, before the crisis, one notch of rating uplift is associated with 20.9% (18.5%) uplift of issuance spread but after the crisis, it is only associated with 5.1% (3.0%) uplift of issuance spread. Such a fall of corresponding spread uplift supports Hypothesis 3-2a. It offers evidence that after the crisis, although investors still react to the ratings offered by CRAs to assess the qualities of ABS, the extent of this reaction has been significantly reduced.

The situation of during-crisis estimators ($\beta_{3-2,3}$ and $\beta_{3-2,5}$) is similar to that of post-crisis estimators, showing a weaker association between ratings and spread during the financial crisis period.

Furthermore, the coefficient $\beta_{3-2,2}$, which is linked to intra-industry competition among CRAs is negative only for the non-MBS dataset and not consistent using different combinations of control variables. It implies that there is only weak evidence to show that investors price a non-MBS security higher (equivalent to a lower issuance spread) if CRAs compete more severely to rate that security (reflected by a larger number of CRAs rating it). In other words, investors 'trust' an ABS more if it is in a more competitive rating background. Such association does not exist in MBS cases. One possible reason is that the variation of the number of CRAs rating MBS is not that significant (most of the MBS are rated by all the three CRAs in my sample) so investors do not observe a significant diversity of industry competition levels on which they can base a decision whether to invest in the MBS security. Although some previous research examines the issue of CRA intra-industry competition in terms of rating quality and issuer preference (Becker and Milbourn, 2008; Dittrich, 2007), to my knowledge, my research is the first to extend the research on the intra-industry competition to the field of market reaction.

Regarding the control variables, most of the estimated coefficients are consistent in MBS and non-MBS datasets and two of them are consistent with the results drawn by Fabozzi and Vink (2012). To save space, I do not display the specific values of those estimators but show the signs of them and their intuitions as follows (details of estimates on control variables are shown in Appendix 3-3):

- Par-amount: consistently negative coefficients imply that investors price an ABS higher if it has a larger issuance volume.
- Coupon rate: consistently positive coefficients imply that investors price an ABS lower if it has a larger coupon rate.
- WAL: consistently positive coefficients imply that investors price an ABS lower if it has a longer weighted average length.
- Issuer size: consistently positive coefficients imply that investors price an ABS lower if its issuer owns a larger market share.
- Credit support: consistently negative coefficients imply that investors price an ABS higher if that ABS has a higher degree of credit support from the issuer.

Table 3-2 Regression result of Equations (3-1) and (3-2)

This table shows the results of Equations (3-1) and (3-2). The dependent variable is logarithm of issuance spread. Number-format Average rating (NR) is the transformed number-format credit rating level indicator based on a formula shown in Table 3-3. Number of CRAs rating the security (N) indicates how many CRAs among the Moody's, Standard & Pools, Fitch and DBRS offer ratings to the tranche. during_crisis (DC) is a dummy variable equal to 1 if the tranche was issued during the financial crisis period (Sep.1st, 2007-Dec.31st, 2009), to 0 otherwise. post_crisis (PC) is a dummy variable equal to 1 if the tranche was issued after the financial crisis period (after Dec.31st, 2009), to 0 otherwise.
The three levels of control variables are defined in Table 3-2.
Regressions are estimated using OLS method.
***the coefficient is significant at 1% level
**the coefficient is significant at 5% level
*the coefficient is significant at 10% level
The figures in the bracket show the corresponding t-statistic
To deal with the heteroscedasticity issue, parallel regressions are run clustering standard errors by three levels respectively: collateral type, issuance year and issuance country. The results do not change significantly.

	Non-MBS						MBS					
Column	A-Equation (3-1)			B- Equation (3-2)			C- Equation (3-1)			D- Equation (3-2)		
Number-format Average rating (NR)	0.07***	0.12***	0.14***	0.17***	0.23***	0.18***	0.17***	0.16***	0.16***	0.19***	0.20***	0.19***
	(6.23)	(11.22)	(70.73)	(11.37)	(18.92)	(87.34)	(36.70)	(41.33)	(60.67)	(48.98)	(42.28)	(70.59)
Number of CRAs rating the security (N)	0.06	-0.02	-0.03**	0.02	-0.04	-0.05***	-0.01	-0.04*	-0.02	-0.01	-0.002	-0.003
	(1.16)	(-0.52)	(-2.39)	(0.43)	(-0.95)	(-4.23)	(-0.57)	(-1.92)	(-1.59)	(-0.46)	(-0.07)	(-0.23)
during_crisis (DC)		--	--	1.16***	1.57***	1.42***	--	--	--	1.37***	1.41***	1.45***
				(8.57)	(12.26)	(37.69)				(16.47)	(13.52)	(22.13)
post_crisis (PC)		--	--	1.18***	1.64***	1.92***	--	--	--	1.01***	1.20***	1.27***
				(3.40)	(3.47)	(7.32)				(4.98)	(4.39)	(8.91)
NR× DC		--	--	-0.12***	-0.22***	-0.17***	--	--	--	-0.11***	-0.14***	-0.11***
				(-4.98)	(-12.60)	(-30.73)				(-9.89)	(-7.39)	(-11.91)
NR× PC		--	--	-0.14***	-0.21***	-0.15***	--	--	--	-0.14***	-0.14***	-0.16***
				(-8.14)	(-11.18)	(-35.13)				(-16.81)	(-13.75)	(-25.37)
Country Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Level 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Level 2	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Control Level 3	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
N	427	1210	16373	427	1210	16373	2478	3246	7277	2478	3246	7277
Adj. R2	76.08%	60.66%	75.87%	81.15%	67.73%	79.21%	68.94%	64.65%	62.20%	72.81%	69.55%	67.18%

3.5.1.2 Transaction dataset

The results of Equations (3-3) and (3-4) are shown in Table 3-5. For each regression, three time-windows (1-day, 3-day and 5-day) are utilized to measure the length of observation on rating announcement dummies.

For Equation (3-3), designed to test Hypothesis 3-1b, coefficients on event-dummies $dE_{i,t}$, $\beta_{3-3,1}$s are significantly negative whatever the observing time-windows. This supports Hypothesis 3-1b by showing that compared with normal days, margin-event days see negative price returns (reflected by a significant price fall).

When considering the absolute values of those negative coefficients among the three windows, I find a negative correlation between absolute values and lengths of time windows (0.38 for the 1-day window, 0.21 for the 3-day and the 5-day window). This can be understood as evidence of recovery-effects of credit rating announcements: after a negative announcement is released to the market by CRAs, investors immediately respond to it by shorting the security at once, then later when the market calms down, the prices take a few days to return to a relatively rational level.

For Equation (3-4) (Hypothesis 3-2b), the coefficients on interaction terms $dP_{i,t} \times dE_{i,t}$, δs are significantly positive whatever the observing time-windows are. This supports the statement of Hypothesis 3-2b by showing a smaller price decrease following negative rating announcements after the financial crisis compared to the pre-crisis period.

3.5.2 Robustness tests

Six robustness tests are conducted to enhance the creditworthiness of my empirical results. The first two tests are designed for the issuance dataset section and the remaining four are designed for the secondary market dataset.

3.5.2.1 Issuance dataset section robustness tests

There are two robustness tests for the primary market data. Robustness test 1 excludes AAA-tranches and Robustness test 2 transforms the number-format rating indicator (NR) into 20 letter-format rating indicators (LR).

Robustness test 1: Test of non-AAA tranches

In the structured finance market, the regulatory policies for AAA-rated ABSs are different from those for non AAA-rated ones (Griffin et al. 2011). In addition, AAA-rated ABS comprise more than 80% of all ABS (shown in Table 3-6). Therefore, it may be that the significant estimated coefficients in Equations (3-1) and (3-2) are derived mainly from different situations between AAA tranches and non-AAA ones but not from all tranche variations. To eliminate the effects of AAA tranches, I exclude them from the datasets and re-run Equations (3-1) and (3-2) to demonstrate results in non-AAA securities.

Table 3-3 Regression result of Equations (3-3) and (3-4)

This table shows the regression results of Equation (3-3) and Equation (3-4). The dependent variable is daily price return (price at exact day minus price at one day before). Regressions are estimated using fixed-effect panel method. dE is equal to 1 if the observation happens in certain days (1, 3 or 5) after a negative rating event happens and 0 otherwise. dP is equal to 1 if the observation happens after Sep 15th 2007 and 0 otherwise. ***the coefficient is significant at 1% level;**the coefficient is significant at 5% level; *the coefficient is significant at 10% level. The figures in the bracket show the corresponding t-statistic.

		Time windows					
		1 day		3 days		5 days	
Variables	Coefficient Descriptor	Eq (3)	Eq (4)	Eq (3)	Eq (4)	Eq (3)	Eq (4)
Event dummy (dE)	$\beta_{3-3,1}$ or $\beta_{3-4,1}$	-0.38*** (-5.71)	-0.54*** (-6.72)	-0.21*** (-5.43)	-0.33*** (-7.03)	-0.21*** (-6.96)	-0.28*** (-7.52)
Post-crisis dummy (dP)	$\beta_{3-4,2}$	--	0.007 (0.45)	--	0.007 (0.45)	--	0.007 (0.45)
dP × dE	δ_{3-4}	--	0.51*** (3.54)	--	0.38*** (4.53)	--	0.21*** (3.15)
Security Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes
Rating-level Control		Yes	Yes	Yes	Yes	Yes	Yes
Index Return Control		Yes	Yes	Yes	Yes	Yes	Yes
T		3914	3914	3914	3914	3914	3914
N		72	72	72	72	72	72
R^2		0.24%	0.24%	0.24%	0.25%	0.25%	0.25%

Table 3-4 Volume proportion of AAA and non-AAA tranches

	MBS dataset	Non-MBS dataset
Proportion of AAA tranches volume	82.45%	80.72%
Proportion of non-AAA tranches volume	17.55%	19.23%

To save space, I have put the updated regression results in the Appendix (Appendix 3-4). I find that for both the MBS sample and non-MBS sample, signs of all key variables in robustness test results are consistent with those in my original tests. The result shows that the (non-) ABS market reaction to credit ratings is significant even when I exclude top-rated tranches.

Robustness test 2: Substituting dummy variables for number-format variables to indicate credit rating notches

One potential shortcoming of Equations (3-1) and (3-2) is the transformation of letter-format ratings to number-format ratings. Such linear transformation is based on the assumption that the rating notch implication is linearly distributed according to the CRAs' opinion (for example, the transformation assumes that the difference in the CRAs' rating opinion difference between AAA and AA is similar to that difference between AA and A, A and BBB etc.). This assumption may not be the case in the market. Moreover, such linear transformation uses one variable representing all of the 21 rating notches and ignores how each of these notches influences the issuance spread. Therefore, in the robustness test 2, I use 20 dummy variables (LR in Table 3), substituting the number-format rating variable (NR) and setting top rating AAA as the benchmark. The details of the transformation from number-format ratings to letter-format ratings (dummies) are shown in Table 3-3 and the new regression equations are shown in Equations (3-6) and (3-7).

$$\ln(spread_i) = \alpha_{3-6,i} + \sum_{m=1}^{20} \beta_{3-6,m} LR_{m,i} + \beta_{3-6,21} N_i + \sum_{p=1}^{P} \beta_{3-6,(p+20)} C_{pi} + \varepsilon_i \qquad (3-6)$$

$$\ln(spread_i) = \alpha_{3-7,i} + \sum_{m=1}^{20} \beta_{3-7,m} LR_{m,i} + \beta_{3-7,21} N_i + \beta_{3-7,22} DC_i + \beta_{3-7,23} PC_i + \sum_{m=1}^{20} \beta_{3-7,(m+23)} (LR_{m,i} \times DC_i) + \sum_{m=1}^{20} \beta_{3-7,(m+43)} (LR_{m,i} \times PC_i) + \sum_{p=1}^{P} \beta_{3-7,(p+63)} C_{pi} + \varepsilon_i \qquad (3-7)$$

Here is the interpretation of $\beta_{3-6,1}$ ($\beta_{3-7,1}$) to $\beta_{3-6,20}$ ($\beta_{3-7,20}$) in Equations (3-6) and (3-7). Each β (for example, $\beta_{3-6,1}$ or $\beta_{3-7,1}$) refers to the spread difference of the corresponding rating notch (for example, AA) compared to AAA rating, the benchmark notch after controlling the tranche characteristics. The interpretation of $\beta_{3-7,24}$ to $\beta_{3-7,43}$ and $\beta_{3-7,44}$ to $\beta_{3-7,63}$ in Equation (3-7) is similar to the previous group of coefficients: they refer to the change of the spread difference of the corresponding rating notch (for example, AA) compared to the AAA rating, the benchmark notch before and during/after the financial crisis when controlling for the tranche characteristics.

I plot the coefficients of Equation (3-6) regarding different rating notches in Figure 3-2 and Figure 3-3 for non-MBS and MBS samples respectively (The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset).

Most of the coefficients on a series of notch dummies (from AA-dummy to C-dummy) are positive, which is consistent with positive β_1 in Equation (3-1). Positive LR coefficients can be interpreted in the following way: compared with benchmark notch

(AAA), other notches are correlated to higher issuance spread (lower prices). They collectively indicate a market reaction to issuance ratings provided by CRAs.

For both MBS and non-MBS lines, a rising trend of dummy coefficient values with decreasing rating notches (increasing NR equivalently) is observed in the Figure 3-2 and Figure 3-3. This means that the lower the rating, the greater the issuance spread difference between the corresponding rating and the benchmark (AAA) rating. This is consistent with Hypothesis 3-1a, according to which lower ratings are associated with higher spread (lower prices).

Figures 3-4, 3-5, 3-6 and 3-7 show coefficients of Equation (3-7). In Figure 3-4 and Figure 3-5, I display details of those coefficients on the interaction terms between during-crisis dummy and dummies indicating different rating notches. In Figure 3-6 and Figure 3-7, I show the coefficients on the interaction terms between post-crisis dummy and dummies indicating different rating notches.

Most of the coefficients on the interaction terms between rating-dummies and post (during)-crisis dummy are negative, which is consistent with negative β_{3-6} (β_{3-5}) in Equation (3-2). They can be interpreted as average differences of β_{3-1} after (during) the financial crisis compared with before the crisis. Thus, negative coefficients indicate that the size of β_{3-1} decreases after (during) the crisis, a possible reflection of the decreased market reaction to CRAs.

It can also be observed in the figures that the sizes of negative coefficients (in Figures 3-4 to 3-7) are more significant in the limit area between investment and non-investment grades than in other areas, particularly Baa1 to Ba3 grades. Since investors are sensitive to ratings near the boundary between investment and non-investment grades, large negative coefficients indicate that the market reaction to credit ratings decreases significantly in this sensitive area.

Figure 3-2 Regression coefficients in Equation 3-6 (Non-MBS)

This figure demonstrates the regression coefficients on letter-format rating indicator (LRs) dummies in Equation (3-6) for the non-MBS dataset. The horizontal axis shows the LR in Equation (3-6) and the vertical axis shows the corresponding regression coefficients on the LR. Lines with different format represent the results of different combinations of control variables. The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset

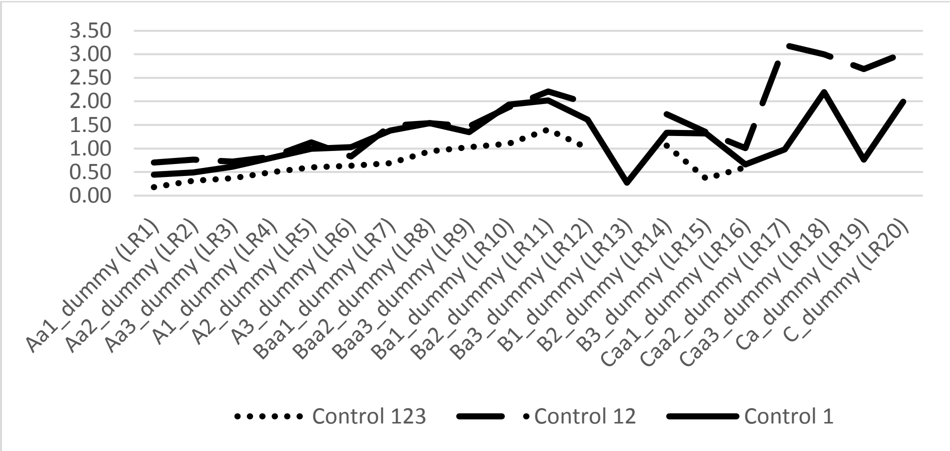


Figure 3-3 Regression coefficients in Equation 3-6 (MBS)

This figure demonstrates the regression coefficients on letter-format rating indicator (LRs) dummies in Equation (3-6) for the MBS dataset. The horizontal axis shows the LR in Equation (3-6) and the vertical axis shows the corresponding regression coefficients on the LR. Lines with different format represent the results of different combinations of control variables. The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset.

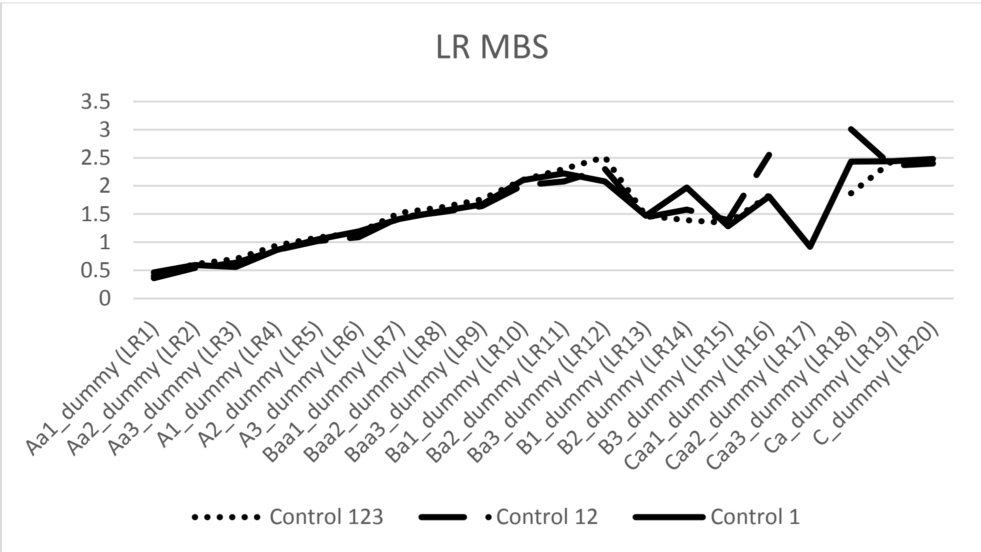


Figure 3-4 Regression coefficients (during crisis) in Equation 3-7 (Non-MBS)

This figure demonstrates the regression coefficients on interaction terms between letter-format rating indicator (LR) dummies and during-crisis dummy in Equation (3-7) for the non-MBS dataset. The horizontal axis shows the LR in Equation (3-7) and the vertical axis shows the corresponding regression coefficients on the interaction terms between the LR and post-crisis dummy. Lines with different format represent the results of different combinations of control variables. The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset.

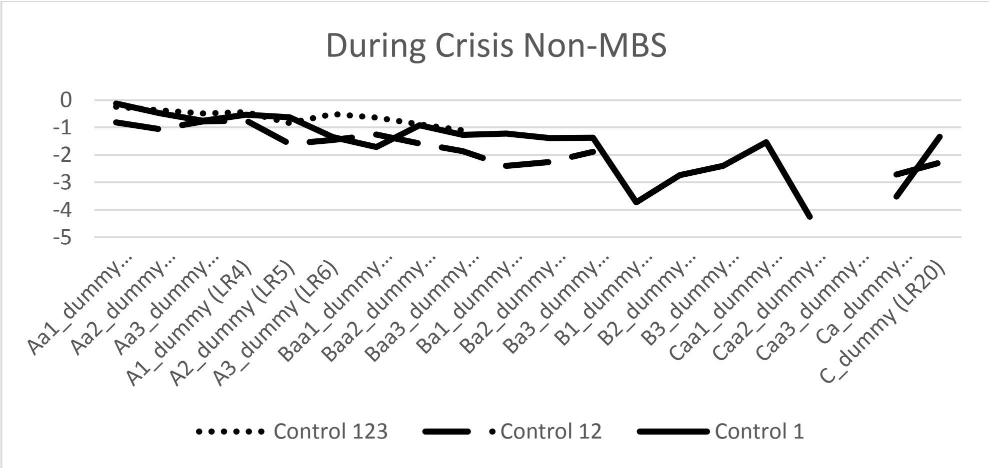


Figure 3-5 Regression coefficients (during crisis) in Equation 3-7 (MBS)

This figure demonstrates the regression coefficients on interaction terms between letter-format rating indicator (LR) dummies and during-crisis dummy in Equation (3-7) for the MBS dataset. The horizontal axis shows the LR in Equation (3-7) and the vertical axis shows the corresponding regression coefficients on the interaction terms between the LR and post-crisis dummy. Lines with different format represent the results of different combinations of control variables. The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset.

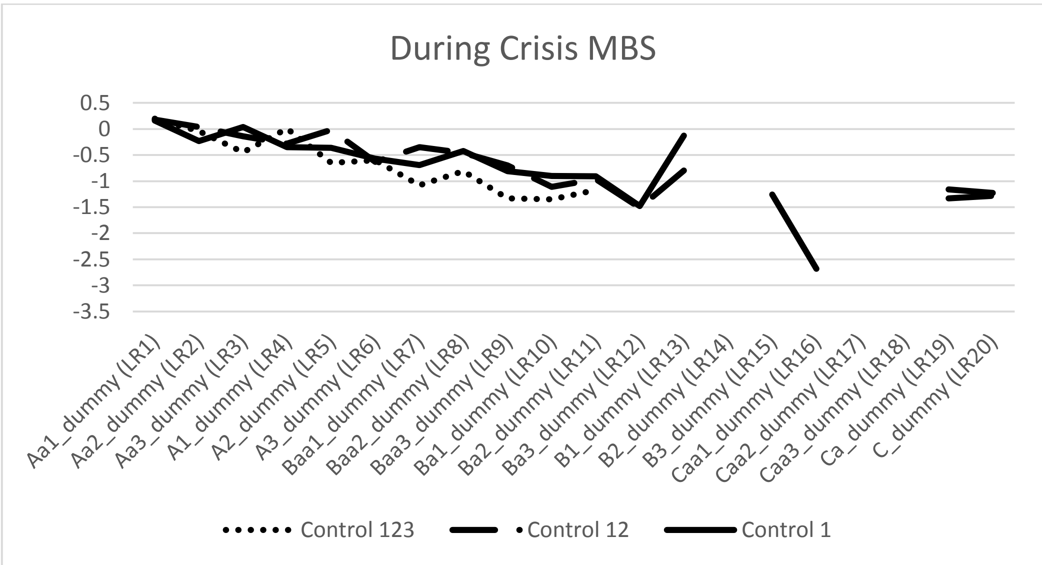


Figure 3-6 Regression coefficients (post crisis) in Equation 3-7 (Non-MBS)

This figure demonstrates the regression coefficients on interaction terms between letter-format rating indicator (LR) dummies and post-crisis dummy in Equation (3-7) for the non-MBS dataset. The horizontal axis shows the LR in Equation (3-7) and the vertical axis shows the corresponding regression coefficients on the interaction terms between the LR and post-crisis dummy. Lines with different format represent the results of different combinations of control variables. The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset.

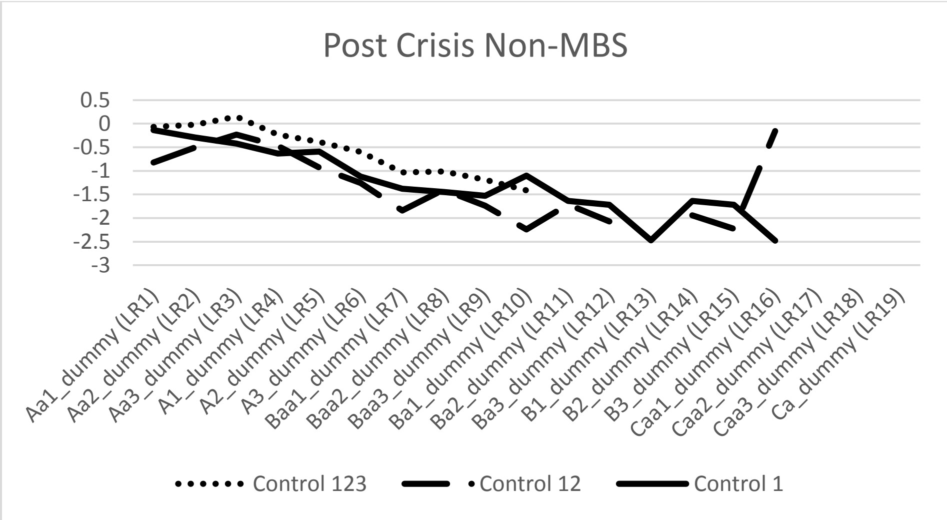
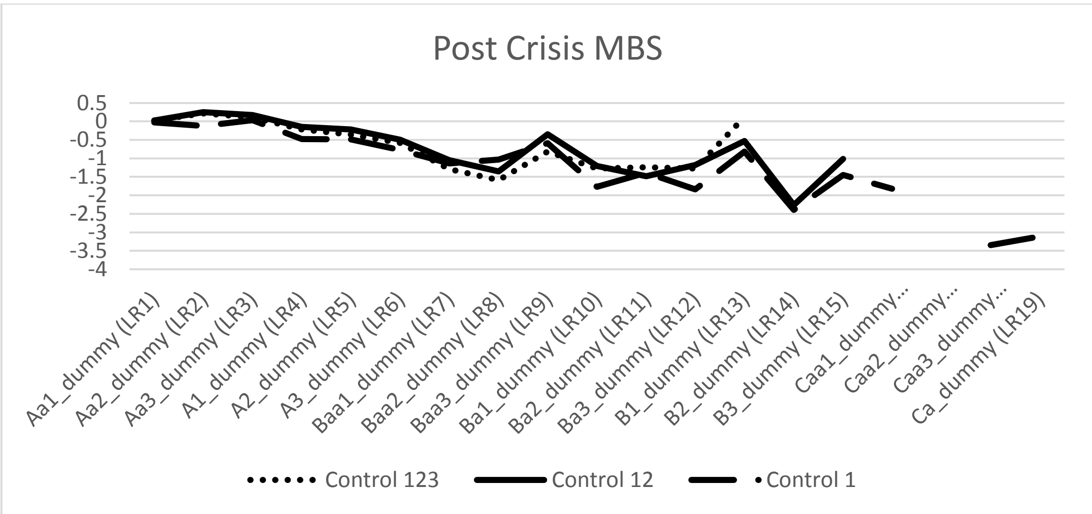


Figure 3-7 Regression coefficients (post crisis) in Equation 3-7 (MBS)

This figure demonstrates the regression coefficients on interaction terms between letter-format rating indicator (LR) dummies and post-crisis dummy in Equation (3-7) for the MBS dataset. The horizontal axis shows the LR in Equation (3-7) and the vertical axis shows the corresponding regression coefficients on the interaction terms between the LR and post-crisis dummy. Lines with different format represent the results of different combinations of control variables. The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset.



3.5.2.2 Transaction dataset section robustness tests

For the second part of my robustness check, four tests are conducted: re-classifying pre-crisis and post-crisis observations, replacing $dE_{i,t}$ by $CD_{i,t}$, excluding 'anticipated' actual downgrades and ruling out market factors.

Robustness test 3: Boundaries between pre-crisis and post-crisis periods

One of the key variables in Equation (3-4) is $dP_{i,t}$which indicates whether the credit rating announcements were released before or after the financial crisis. Obviously, the definition of when the 2007/2008 global financial crisis starts determines the setting of $dP_{i,t}$. In the baseline model I set September 2007 as the assumed boundary. This is consistent with the fact that the sub-prime crisis is recognized as having started in the summer of 2007 (Orlowski, 2008) as well as the fact that the Federal Reserve started to take action in response to the crisis in September 2007 (Cecchetti, 2009). However, there are some stages for the financial crisis to emerge, develop and deteriorate and the key dates of the stages range from 2007 to 2010 (Elliott, 2011). Therefore, I re-set $dP_{i,t}$ by changing the boundary to September 2008 and other later time points to check whether the results are significantly reversed.

For Equation (3-4), I re-define $dP_{i,t}$ by resetting the boundaries of pre-and post-crisis periods. The pre-set boundary is September 2007 while other boundaries are set once every two months ranging from September 2008 (Lehman Brothers' fall) to the end of 2009. To save space, I have put the regression details for different boundary settings in the Appendix (Appendix 3-5). The coefficient of interest, δ, remains significant if the boundary is set between September 2008 and March 2009. Beyond the 'significant area' (from May 2009 to November 2009), δ becomes insignificant. In sum, it shows that my result is robust if I view any point in the period 2007.09-2009.03 as the boundary between pre-and post-crisis periods. This finding accords with common sense that the global financial crisis occurs before March 2009.

Robustness test 4: Substituting 'rating-change degree' for 'event dummy' to indicate effects of rating announcements

In Equations (3-3) and (3-4), I use $dE_{i,t}$, a dummy variable to discriminate observations around the rating announcements from normal observations without the effects of rating announcements. However, such a setting only considers the occurrence of those announcements but does not imply the notch degrees involved in the announcements. In other words, the event-dummy indication assumes equal effects of different downgrade degrees and even 'possible downgrade', a warning signal, but with no actual downgrade. To address potential bias caused by the event-dummy setting, I re-run Equations (3-3) and (3-4), replacing $dE_{i,t}$ with $CD_{i,t}$ (short for 'Change Degree') indicating by how many notches they were downgraded by the rating announcements. The updated equations are shown in (3-8) and (9):

$$return_{i,t} = \alpha_{3-8,i} + \beta_{3-8,1} \times CD_{i,t} + u_{i,t} \qquad (3-8)$$

$$return_{i,t} = \alpha_{3-9,i} + \beta_{3-9,1} \times CD_{i,t} + \beta_{3-9,2} \times dP_{i,t} + \delta_{3-9} \times \left(dP_{i,t} \times CD_{i,t}\right) + u_{i,t} \qquad (3-9)$$

$\beta_{3-8,1}$ and $\beta_{3-9,1}$both Equations (3-8) and (3-9) indicate how much the average price return change is, following one notch of rating downgrade from Moody's. Further, δ_{3-9} in Equation (3-9) indicates the average change of the degree of $\beta_{3-9,1}$ after the financial crisis compared with the pre-crisis period.

The cost of replacing $dE_{i,t}$ with $CD_{i,t}$ is that the latter can only identify 'actual downgrades' but not 'possible downgrades' because with a 'possible downgrade announcement', CRAs do not in fact downgrade the security thus the degree of $CD_{i,t}$ is 0 (but $dE_{i,t}$ for the same announcement is 1 but not 0). Therefore, with $CD_{i,t}$ the 'possible downgrade' announcements are equal to the circumstance with no events occurring.

Replacing $dE_{i,t}$ by $CD_{i,t}$, I run Equations (3-8) and (3-9). To save space the regression tables are put in the Appendix (Appendix 3-6). In Equation (3-8), the estimated coefficients on $CD_{i,t}$ ($\beta_{3-8,1}$) are negative except for the shortest window (1 day). They imply that the more notches CRAs downgrade, the larger is the size of the falloff in that ABS's price. It indicates that when making decisions on buying or selling an ABS, investors consider not only whether it is downgraded but also by how many notches it is downgraded. This finding enhances the conclusion regarding Hypothesis 3-2a. In Equation (3-9), estimated coefficients on interaction terms (δ_{3-9}) are positive, which is equivalent to a lower absolute value of post-crisis $\beta_{3-9,1}$. It shows that the degree of $CD_{i,t}$'s effects on price returns is weaker after the crisis, consistent with the statement of Hypothesis 3-2b. However, the negative signs are not consistently significant in Equation (3-9), which contradicts the results of Equation (3-4). The reason may be that replacing *dE* by *CD* reduces the number of events in the testing sample, particularly in the post-crisis sample.

Robustness test 5: Considering anticipated downgrade announcements

Creighton et al. (2007) state that an actual downgrade announcement should be categorized as 'anticipated' if it comes following a possible downgrade announcement. If a possible downgrade announcement is released on a certain security, it shows a negative signal from CRAs that they may downgrade it at some time in a near future. Investors have a different understanding of the security if they receive such signals than if there are no downgrade warnings. Therefore, it is reasonable to assume that when an actual downgrade comes, investors have already prepared for, or 'anticipated' that bad news and may have different strategies from those adopted in normal downgrades.

I regard actual downgrade announcements which are released within a 3-month time after a possible downgrade announcement as 'anticipated' and others as ‘unanticipated’. I then run the Equations (3-10) and (3-11) to enhance Equations (3-3) and (3-4) respectively.

$$return_{i,t} = \alpha_{3-10,i} + \beta_{3-10,1} \times ADE_{i,t} + \beta_{3-10,2} \times UDE_{i,t} + u_{i,t} \qquad (3-10)$$

$$return_{i,t} = \alpha_{3-11,i} + \beta_{3-11,1} \times ADE_{i,t} + \beta_{3-11,2} \times UDE_{i,t} + \beta_{3-11,3} \times DP_{i,t} + \delta_{3-11,1} \times (DP_{i,t} \times ADE_{i,t}) + \delta_{3-11,2} \times (DP_{i,t} \times UDE_{i,t}) + u_{i,t} \quad (3-11)$$

$ADE_{i,t}$ (anticipated dE) is a dummy equal to 1 if at the day *t*, the security *i* is within the pre-defined time windows (1 day, 3 days or 5 days) after an anticipated negative rating event occurs and 0 otherwise. $UDE_{i,t}$ (unanticipated dE) is a dummy equal to 1 if on the day *t*, the security *i* is within the pre-defined time windows (1 day, 3 days or 5 days) after an unanticipated negative rating event occurs and 0 otherwise.

Results for the re-run regressions considering anticipated downgrades are shown in the Appendix (Appendix 3-7). Coefficients on UDE ($\beta_{3-10,2}$ and $\beta_{3-11,2}$) are significantly negative and those on the interaction terms between dP and UDE ($\delta_{3-11,2}$) are significantly positive. This is consistent with the result of Equations (3-3) and (3-4). However, I find insignificant estimators on ADE ($\beta_{3-10,1}$and $\beta_{3-11,1}$) as well as corresponding interaction term ($\delta_{3-11,1}$) , showing that if a negative rating announcement is anticipated, the impact of this announcement on the market is not significant. This finding shows that the results obtained in the main tests are only valid if the rating downgrades are unanticipated. This is consistent with the results drawn by Creighton et al.’s (2007) who argue that the impact of anticipated rating revisions is normally significantly lower than that of unanticipated ones.

Robustness test 6: Eliminating the effects of the market

The dependent variable $return_{i,t}$ is the absolute price returns without consideration of market effects. However, the price variations of ABS are a reaction of the combination of market variation and non-market variation (for example, the rating factor). Therefore, a significant price return reaction to negative announcements may be attributed to the market factor but not the announcements themselves.

To eliminate the market effects, I replace the dependent variable with three other indices which take market factor into account. Index 2 and Index 3 are introduced by Brooks et al (2004).

Index 1: Pure daily return excluding market return: $(p_{i,t} - p_{i,t-1}) - (M_{i,t} - M_{i,t-1})$ (M_t is the Barclays ABS market index on day t).

Index 2: Abnormal return. This is the residuals from the regression of price returns with market returns and indicates how the price at day t deviates from its expected price estimated by market index. The Abnormal Return, $AR_{i,t}$ is created according the following steps:

- For each rating event (assuming happening at day 0), run a regression of security return $Return_i$ on market return $Return_m$ for the previous 100-day observations before that event:

$$Return_{i,t} = \alpha + \beta \times Return_{m,t} + \varepsilon \quad \text{(t from -100 to 0)}$$

- Using the estimated β (if β is not significant in the regression, that observation is deleted) , estimated α, and the real market return $Return_{m,t}$ to calculate estimated return before and after the event, $Return_{i,t}$:

  $\widehat{Return}_{i,t} = \hat{\alpha} + \hat{\beta} \times Return_{m,t}$ (t from -100 to +5)

- Calculate 'AR' as the difference between the real security's return and the estimated one:

  $AR_{i,t} = Return_{i,t} - \widehat{Return}_{i,t}$, (t from -100 to +5)

Index 3: Standardized abnormal return: a revised version of AR by standardizing it. $SAR_{i,t}$ is calculated as following:

- For each rating event, collect the estimated residual terms (equal to AR):

$$\widehat{\varepsilon_t} = Return_{i,t} - \hat{\alpha} - \hat{\beta} \times Return_{m,t} = Return_{i,t} - \widehat{Return}_{i,t}$$

- Calculate the variance of residual terms $\sigma^2(\hat{\varepsilon}) = \frac{1}{103} \times \sum_{t=-100}^{+5}(\widehat{\varepsilon_t}^2)$
- Calculate the SAR: $SAR_{i,t} = \frac{AR_{i,t}}{\sqrt{\sigma^2(\hat{\varepsilon})}}$

Updated regression results are shown in the Appendix (Appendix 3-8). I find similar results with the original regressions of Equations (3-3) and (3-4). $\beta_{3-12,1}$and $\beta_{3-13,1}$is significantly negative and δ_{3-13} is significantly positive, no matter which index and which time window I use. A recovery effect can also be observed for each index (longer time windows, smaller size of $\beta_{3-13,1}$).

In sum, my result for the secondary market dataset passes all four robustness tests despite some minor variations.

3.6 Conclusion

This paper is an empirical study on the ABS market reaction to credit ratings. Two hypotheses are proposed. One posits the existence of ABS market reaction to the opinions provided by CRAs and the other proposes that such reaction has weakened since the global financial crisis. For each hypothesis, there are two sub-hypotheses, focusing separately on data from the primary and secondary markets. Assumptions about the rating implication stability on the primary market and the liquidity stability of the secondary market are tested and supported. I collect unique samples for both markets, using the market information from Bloomberg and the Thomson Database as well as the rating information from Moody’s official website. The approach to studying primary (secondary) market data is cross-sectional (panel) regression analysis.

By the data analyses, I find evidence to support both hypotheses. The empirical results are compatible to the existence of market reactions to credit ratings (Hypothesis 3-1) by showing that initial ratings impact ABS issuance spread (prices) and that negative rating announcements from CRAs have an immediate shock on ABS transaction prices. In addition, the empirical results demonstrate a weaker reaction in the post-crisis period through a weaker relationship between ABS issuance spread (transaction prices) and the initial ratings (rating announcements) from CRAs (Hypothesis 3-2). Moreover, other related results are observed, such as the relationship between intra-industry competition of CRAs and investors' confidence on ratings and investors' 'recovery-effects' of their reactions to negative rating announcements.

Several robustness tests are conducted to ensure the consistency of the above empirical results. Those checks include the following areas: excluding top-rated tranches, using 20 dummies to indicate rating notches, changing definitions on when the financial crisis started, studying the changes in degrees of ratings announced by CRAs, keeping only unanticipated rating events and eliminating the market factors from price returns.

I briefly discuss the possible theoretical reasons behind those observed empirical results. The reaction of ABS investors to ratings provided by CRAs can be attributed to the complexity of structured finance products, rating-based regulations and the CRAs' long-term reputations. The trend of weaker reaction can be explained by the chaos of the structured finance market due to the financial crisis, regulators' efforts to remove credit ratings from regulatory activities (Dodd-Frank Act) and the damage done to the reputation of CRAs due to their poor performances in the crisis. However, this paper does not offer a detailed discussion on these theoretical reasons and leaves this gap for further research.

My research in this chapter cannot fully tease out all the changed factors before and after the financial crisis and exclude them from the analysis of credit rating reforms. Specifically, the same rating notch may have implied different risks since the crisis and the ABS secondary market liquidity may have been seriously fallen since the crisis. Although I did some tests to respond these two criticism, the evidence is not strong enough to tackle these two questions.

Last but not least, the data analysis results should be interpreted in the way of ‘association’ between ratings and ABS prices rather than ‘causal relationship’ from ratings to ABS prices (See Hypothesis 3-1). In other words, although the results cannot reject the statement that ABS prices are affected by credit ratings, it cannot be fully proved by my analysis. In addition, the methods used in this chapter only investigate whether the rating-price link has diminished after the crisis but cannot figure out whether it is the financial crisis which ‘causes’ this change.

4 Chapter IV: Is solicitation status related to rating conservatism and rating quality?

“This salient conflict of interest permeates all levels of employment, from entry-level analyst to the chairman and chief executive officer of Moody's corporation.”

-- William Harrington, former executive of Moody’s, 2011

4.1 Introduction

The conflict of interests is a widely-discussed topic in the field of credit ratings. From an international perspective, the rating industry presents a feature of oligopoly (by ‘Big Three’ agencies: Moody’s, S&P and Fitch) and hence it is commonly criticized, as the Big Three CRAs would have the motivation to make extra profits by taking advantage of their oligopolistic position.

The center of the topic of conflict of interests is the rating service fee. The rating fee payment model and its relation to rating performances are regarded among the key measures of conflict of interest (Fulghieri et al., 2013; Kashyap and Kovrijnykh, 2015). All the Big Three CRAs follow the ‘issuer-paid’ model of rating service collection. In this model, firms who would like to issue debt/equity should pay all the service fees to credit rating agencies to request agencies to issue ratings for them. Some criticism is raised about whether such a payment model may allow the CRAs who act as oligopolists to ‘sell’ their rating services to issuers. In other words, in the framework of the issuer-paid model, credit rating agencies have the incentives to issue over-optimistic ratings for those firms who purchase their rating services. Previous literature has two points of penetrations for the study of conflict of interests in terms of rating payment model: special cases of CRAs with an ‘investor-paid’ model and the regime of the ratings by ‘issuer-paid’ CRAs.

Some innovative rating agencies, apart from the Big Three, follow the ‘investor-paid’ model where the investors who are interested in the rated firms’ performances subscribe to the rating reports issued by the rating agencies. Among the 9 NRSRO

CRAs, one agency called *Egan-Jones Rating Company* applies the investor-paid business model. Some small CRAs also follow this new payment model, such as *Chengxin Credit Management Co* (China), *Universal Credit* Ratings Group (China) and RusRatings (Russia). The reason that investor-paid CRAs are established is mainly to 'defeat' traditional big CRAs by 'support(ing) the funding ecosystem which has so severely broken down' and by preventing the serious 'rating shopping' before the 2008 financial crisis (Sean Egan, founder of Egan-Jones Rating Company, 2008). In terms of scholars' views, conflict of interests is examined by investigating the ratings given by agencies of both models (Cornaggia and Cornaggia, 2013; Bonsall IV, 2014; Xia, 2014). However, research on the impact of payment model on credit rating agencies is restricted by the fact that the comparison has to be made between different rating agencies so the results of the comparison may be driven by the unobservable characteristics gap between the agencies. In this paper, I study the topic of conflict of interests from another perspective: the unsolicited rating regime. This regime is applied by the Big Three agencies as an essential supplemental service: different from the majority of cases where the agency collects fees from rated firms, the agency selects for rating some of the firms who neither request the agency for rating services nor pay any fees to it. Whether CRAs follow the double standard in issuing ratings for firms who pay them or not is viewed as an indicator of conflict of interest. Literature has identified that generally credit rating agencies issue more conservative ratings for unsolicited rating recipients who do not request or pay for the rating services (Byoun and Shin, 2002; Poon, 2003; Poon et al., 2009; Bannier et al., 2009). However, this finding does not necessarily prove that there exists a conflict of interest unless evidence is provided to show that the more conservative ratings issued for unsolicited rating recipients are biased.

To answer the question about whether the conservatism for unsolicited ratings is biased, scholars raise two contrary hypotheses (Byoun et al., 2014): the strategic behavior hypothesis and the self-selection hypothesis. The former hypothesis states that the more conservative unsolicited ratings are biased and reflect a strategic behavior of rating agencies who offer over-optimistic ratings for those firms paying them in order to either compensate the firms who buy their services or blackmail the firms who do not pay. The contrasting hypothesis, self-selection hypothesis, states that it is the firms who select not to purchase rating services from rating agencies because of their concerns about weak firm characteristics which have not been observed by the market, but may be made public to the market once the firms opt to be rated. Rating agencies capture this self-selection incentive of the firms and rate them without being paid in order to provide transparency to market participants. To reflect the conservatism towards the weak characteristics of unsolicited rating recipients, rating agencies generally issue relatively lower ratings for those firms than for normal (solicited) rated firms.

In this paper, I focus on the Moody's rating data and provide empirical evidence to enhance the hypothesis of self-selection by showing two facts: 1) the rating levels by Moody's issued to firms who do not request solicited rating services are more conservative than those issued to firms who request the solicited rating services; 2) the rating quality of both types of ratings do not have significant difference. The first finding provides a necessary condition for the self-selection hypothesis and demonstrates that rating agencies observe firms' self-selection incentives and rate them lower. The second finding provides a sufficient condition for the hypothesis and shows that those lower unsolicited ratings are not biased but have the same rating quality of solicited ones, reflected by same default risk predictability and same rating action timeliness.

The research in this paper contributes to the literature from the following perspectives. 1) I supplement the comparison between Moody's solicited and unsolicited ratings, by not only taking rating levels into consideration but also testing the ex-post measurement of rating quality of the two types of ratings. The rating level is only an ex-ante forecast of firms' risk of default and cannot reach the self-selection hypothesis without the finding of no significant gaps of ex-post measures of the quality between unsolicited and solicited ratings. In this paper, I apply the ex-post measure to assess how Moody's ratings 'predict' the reality and how timely the rating actions are to reflect the 'rating quality'.

2) For the test of rating level gaps between solicited and unsolicited ratings, I supplement the comparison of two types of ratings issued by Moody's by introducing rating gaps between Moody's and the other two big CRAs (S&P and Fitch). To examine the impact of solicitation status on rating levels, the literature focuses on the ratings issued by a single rating agency, splits those ratings based on the solicitation status and compares those two groups of ratings (Byoun and Shin, 2002; Poon, 2003; Poon and Firth, 2005; Bannier et al., 2008; Poon et al., 2009; Bannier et al, 2009; Byoun et al., 2014). To enhance these analyses, I introduce a 'difference-in-difference' method to imply solicitation's impact: the first layer of difference which is between Moody's and S&P/Fitch rating levels while the second layer captures whether Moody's-S&P/Fitch rating gaps vary with different solicitation statues. The introduction of D-i-D analysis extends the scope of investigation of 'absolute rating level' (the exact rating level) gaps by studying the 'relative rating level' (rating gaps between Moody's and the other two agencies) gaps. Both the single-agency test and multi-agency test show persistent results that unsolicited ratings of Moody's are lower than solicited ones.

3) I amend the scope of ex-post measures of rating quality, using Distance to Default (DTD) and rating timeliness.

DTD is applied to indicate the predictability of Moody's ratings in terms of the actual variation of default risk following ratings in different levels. I show evidence of an absence of the impact of solicitation status on DTD predictability (essential to prove the self-selection hypothesis) by two findings, as follows. 1) Ratings at same levels are followed by statistically similar DTD performances regardless of the solicitation status of the rated firms; 2) I use solicited ratings and fundamental information of corresponding firms to model the actual DTD, obtain coefficients on rating levels (with other fundamental variables), apply those coefficients to actual unsolicited rating levels and fundamentals to calculate the predicted DTD, and find no significant gap between the predicted and observed DTDs of unsolicited ratings.

The information on the lead-lag relationship between rating agencies' actions is collected and analyzed to reflect timeliness of Moody's unsolicited/solicited ratings, which is another measure of the rating quality (Berwart et al., 2016). Moody's rating actions which occur no more than 90 days before (after) S&P/Fitch take actions are defined as 'lead' ('lag'). I measure the speed of rating actions by considering the ratio/likelihood of 'lead' or 'lag' actions of Moody's out of all observed actions. By comparing unsolicited and solicited ratings, I find no significantly different rating timeliness, except some very weak evidence of a lower rating quality of unsolicited ratings.

This paper is structured as follows. In Section 4.2, I describe the background of unsolicited rating regime of Moody's, demonstrate the motivation of the study on unsolicited ratings and raise the self-selection hypothesis of conservative unsolicited and present the related literature. Section 4.3 is a theoretical model to provide a background of empirical tests and a presentation of the main hypotheses. Section 4.4 describes the data source, data matching scheme, and the setting of some essential variables. In Section 4.5, a series of empirical analysis methods are applied to test the self-selection hypotheses and Section 4.6 concludes this paper.

4.2 Background and literature review

4.2.1 Background

Historically, Moody's has issued unsolicited ratings since its establishment in 1909. However, it started publicly announcing the identification of unsolicited firms in 1999. Despite the frequent complaints and investigations (Jefferson County case, 1983; US Justice Department case, 1996; Hannover Re case, 2004), Moody's claims that the activity of issuing unsolicited ratings is intended 'to provide greater transparency to market participants' and the rating agency 'reserves the right' to issue them 'not at the request of the rated equity and /or its agents' (Moody's, 2018).

Different from traditional solicited ratings, unsolicited ones have two unique features: fee payment and information access. Moody's does not collect the list fee from rated firms for the issuance of unsolicited ratings and does not have access to internal information of rated firms by negotiation.

Moody's does not publicly list any factors related to profits (the center of the criticism of conflict of interest) as criteria to select firms for whom they issue unsolicited ratings. The criteria they list are: benefits to market participants, issuers' size, the issuance time of the issuers and relevance to other firms Moody's rates.

In terms of the information access, in Moody's documents (Moody's, 2018) it says '(the) publication of an unsolicited credit rating will be conditioned, among other factors, on its determination that sufficient information is available to allow MIS[14] to assign and maintain the credit rating'. On the other hand, it also states that 'a rated entity does not have the ability to decline publication of an unsolicited credit rating', which implies that there is no negotiation between the rated firm and Moody's. Due to the absence of negotiation, Moody's should not have access to internal information of the rated firms guaranteed by formal commercial contracts.

[14] MIS: short for 'Moody's Investors Service'

Although Moody's claims that it 'does not distinguish between solicited and unsolicited credit ratings with respect to its credit rating methodologies' to show its fairness and absence of bias to the market, the bias of unsolicited ratings related to the fee payment and the lack of internal information are discussed and concerned by both regulators and scholars.

Regulators were skeptical about the issuance of unsolicited ratings due to the payment, which may incur the conflict of interests, and to the lack of information access. However, in the wake of the 2008 global financial crisis, regulators have tended to change their attitudes towards unsolicited ratings and become friendlier. In a policy document issued by SEC regarding credit rating agencies (SEC, 2009), the Commission states that it 'preliminarily believes' CRAs registered as NRSROs (including Moody's) to have sufficient ability to collect non-public information even in the activity of unsolicited rating issuance. Moreover, the Commission regards the mechanism of unsolicited rating issuance as a suggestive way of increasing the competition and pushing rating agencies to be more proficient (SEC, 2009).

There are two streams of academic research which investigate the gap between solicited and unsolicited ratings. One stream focuses on the comparison of levels of unsolicited and solicited ratings to study whether solicited ratings are higher than for unsolicited ones. The majority of literature finds evidence to show that it is the solicited ratings which are more likely to be higher (Byoun and Shin, 2002; Poon, 2003; Poon et al., 2009). However, previous literature only compares the rating levels for different rated firms offered by one rating agency (either S&P or Fitch) to prove that unsolicited ratings are associated with a lower rating level. In this paper, I introduce the split of ratings offered for a firm, but by different rating agencies to enhance my conclusions. Another stream of research concerns the reason for lower unsolicited ratings by exploring the ex-post measures of performances of firms who receive both types of ratings. Two contrary hypotheses are discussed by the literature (Byoun et al., 2014):

- Strategy hypothesis
- Self-selection hypothesis

For the strategy hypothesis, the lower unsolicited ratings are viewed as biased because a significant gap is observed between the ex-post performance measures of the recipients of unsolicited and solicited ratings, given the same rating levels. For example, if the ex-post performances of unsolicited rating recipients are better than their peers given the same level of ex-ante ratings, this indicates that rating agencies 'under-estimate' the quality of unsolicited rating recipients by offering unreasonably lower ratings to them which are not corroborated by ex-post performances. In other words, it is the strategy of rating agencies to issue lower unsolicited ratings systemically. The incentives of rating agencies to offer biased unsolicited ratings are summarized in different aspects: 1) 'blackmail' effect, which is used by rating agencies to 'blackmail' other firms to purchase rating services from them to avoid being offered unsolicited ratings (Fulghieri, 2013); 2) upward bias due to being paid, which means that rating agencies cater to their customers by inflating their ratings (Poon, 2003; Poon and Firth, 2005) and; 3) information access: rating agencies do not have access to internal information of rated firms so they prefer offering more conservative ratings to them to be safe (Bannier et al., 2009).

The literature has widely discussed the strategy hypothesis in the context of conflicts of interests. The existence of a strategic selection of unsolicited ratings by CRAs is a negative signal of their reputation because it implies that the CRAs issue unfair ratings to those firms who do not pay them. However, some scholars (Bannier et al., 2008) discuss the alternative hypothesis, self-selection, which is investigated in this paper.

For the self-selection hypothesis, although unsolicited ratings are lower than solicited ones, they are not regarded as biased. Due to the information asymmetry between firms and investors, firms always know more information about themselves than investors. However, firms' selection of whether or not to solicit the rating services can be observed as a way to infer the actual condition of firms which is not released to the investors. Weak firms select not to solicit the rating services because they know that the rating information released by rating agencies would not be favorable in terms of their aim to attract investors. The rating agencies capture the fact that those firms do not request their rating services and take it as a negative factor when deciding the unsolicited rating levels for the firms. Therefore, rating agencies tend to rate unsolicited rating recipients at a lower level than solicited rating recipients.

If the self-selection hypothesis holds, two phenomena should be observed: 1) rating levels for unsolicited cases should be more conservative than for solicited cases, which reflects rating agencies' reaction to the self-selection incentives of firms and 2) ratings should provide information to the market even though they are unsolicited (the rating quality should be as good as that of solicited ratings).

4.2.2 Literature review

4.2.2.1 Rating Bias

To study the rating bias which is associated with the fee payments, the existing literature mainly focuses on two streams of research: the solicitation and its impact on rating levels and the rating gaps between investor-paid agencies and issuer-paid agencies. In addition, other studies discuss the rating split provided by different rating agencies to imply rating bias.

Solicitation

From the theoretical perspective, some scholars analyze the roles of unsolicited ratings in the rating market. Fulghieri et al. (2013) establish a game-theory model to study the behavior of rating agencies who issue unsolicited ratings, investors who observe past performances of issuers as an evolution of rating quality of rating agencies, and the issuers whose incentive is to obtain favored ratings by rating agencies. In the equilibrium, both the strategic behavior hypothesis and the self-selection hypothesis are supported.

A series of empirical papers discuss the effect of solicitation on the level of credit ratings. The majority of them support the hypothesis of strategic behavior. (Byoun and Shin, 2002; Poon, 2003; Poon and Firth, 2005; Poon et al., 2009; Bannier et al, 2009; Byoun et al., 2014).

Opposite to the aforementioned papers, others support the hypothesis of 'self-selection' which implies that the performances of recipients of unsolicited and solicited ratings should not be significantly different. Poon (2003) shows weak evidence of that by finding that firms receiving unsolicited ratings are more likely to perform poorly than those receiving solicited ratings. Bannier et al (2008) use non-US firms and their ratings by S&P and find that, except banking sector, for all the other firms, ex-post default performances are not related to the status of solicitation.

Besides these two strands of research, some papers mention the market reaction of the rating solicitation. Behr and Guttler (2008) test the stock reactions of the announcements of solicitation and conclude that, even though unsolicited ratings are based on only the public information, they still impact the stock market to some extents. Byoun and Shin (2002) and Han et al. (2013) find similar results for the bond yield cases. Klusak et al., 2017 use the disclosure of sovereign rating solicitation status as a shock to study its market impact. *Payment Model*

Another strand of research investigates the rating bias related to the application of issuer-paid and investor-paid models. Kashyap and Kovrijnykh (2015) establish a game-theory model. Jiang et al. (2012) study the impact of the S&P' s introduction of issuer-paid model in the1970s on its rating levels and find that 'the issuer-pay model leads to higher ratings'. Their research is extended by Bonsall IV (2014) who finds that the implication of issuer-paid models for credit ratings is associated with more optimistic ratings whose predictability is also higher. Except for those papers which focus on only big CRAs in different periods, others compare the performances between big issuer-paid agencies and small innovative investor-paid agencies (Cornaggia and Cornaggia, 2013). Xia (2014) finds that, after EJR (a small investor-paid CRA) enters the market, the information quality of credit ratings provided by S&P has been increased significantly.

Split ratings and lead-lag relationship among CRAs

Split ratings and lead-lag relationship are both for the comparison among CRAs. Split ratings refer the phenomenon that different CRAs offer different ratings for a firm or security. In this chapter I make use of split ratings and examine the gap of ratings between Moody's (the experiment group) and S&P/Fitch (the control group) to show the lower ratings of unsolicited ratings. Lead-lag ratings refer to the phenomenon that some CRAs take rating actions (downgrades, upgrades, outlook, watch list) systematically lower or faster than other CRAs. In this chapter, I take advantage of the lead-lag relationship as a measure of rating quality.

The usage of split ratings and lead-lag analysishas been applied by many scholars. Güttler (2011) shows timelier rating announcements and Moody's is more likely to follow S&P. This result is consistent with the work by Alsakka and ap Gwilym (2010-b) which includes five agencies (Big Three and two local CRAs in Japan) and observing different lead-lag relationships for upgrade and downgrade cases. Besides rating changes, Bowe and Larik (2014) find evidence from US corporation ratings to show specific firm characteristics affect the likelihood of receiving different ratings given by different CRAs. They also find that Moody's is more likely to issue ratings with lower levels than S&P.

4.2.2.2 Rating Quality

The ex-post measurement of the rating quality is an essential component in my analysis. Theoretical papers measure the rating quality in the context of the economic cycle (Bar-Isaac and Shapiro, 2013) while other papers focus on the measurement of the rating quality.

Three categories of rating quality measures are applied in the empirical papers, relative timeliness comparison, the degree of information content, and predictive power of default.

A number of papers view the timeliness (i.e lead-lag relationship among different CRAs) as a relative measure of the rating quality (Güttler, 2011; Berwart et al., 2016). A rating agency is viewed as 'better' if it makes actions prior to its peers. Another type of quality measure concerns how much information the ratings provide. To define the information, scholars use different indices, such as stock returns (Behr and Guttler, 2008; Byoun et al., 2014; Bruno et al., 2015) and bond yields (Han, 2013; Bruno et al., 2015). Moreover, the power of ratings to forecast firms' defaults is regarded as an alternative measure of rating quality by many researchers. Becker and Milbourn (2011) use the default events within a three-year window following credit rating actions to measure the rating quality. Baghai and Becker (2018) analyze the default rates of firms rated at each of the rating levels to imply the predictability of rating agencies. Hilscher and Wilson (2016) update the traditional measurement of the probability of default estimation by applying a concept of 'failure score', by which a series of fundamentals, with or without rating factors are applied to estimate the default events. The rating quality is reflected by a comparison between the baseline score which is established only by fundamentals and the supplemental score which is established not only by fundamentals but adding credit ratings.

In this paper I apply default risk predictability and rating timeliness as indicators of the rating quality. Ratings are issued by CRAs to estimate firms' default risk, therefore, the predictability of default, by its nature, should be considered as an indicator to reflect the rating quality. As for the timeliness, it can be intuitively measured by the lead-lag relationship between one rating agency and another. The reason that I do not use information contents as an indicator is that one of the essential components to measure the information contents is stock returns and some of the firms who receive unsolicited ratings by Moody's are not listed on the secondary market.

4.3 Theoretical model and hypotheses

4.3.1 Theoretical model

In order to illustrate the self-selection hypothesis from a theoretical perspective, I build a simplified theoretical model to reflect how rating agencies react to firms' self-selection of soliciting rating services and how ratings provide information for the market. In the simplified model, the definition of abbreviations is shown as follows.

SL shows the solicitation status; SL=1 means that the rating is solicited and SL=0 means that the rating is unsolicited.

S shows the actual status of the firm. In this model I assume that there are only two statuses of firms: Good (*G*) and Bad (*B*).

CA shows the rating given by rating agencies to the firm. I simplify the model by only assuming two rating notches, 1 and 0. CA=1 indicates that the rating is high and CA=0 indicates that the rating is low.

Furthermore, I assume the given parameters as follows.

$\theta = P(S = G)$

$\tau_1 = P(SL = 1|S = G)$

$\tau_2 = P(SL = 1|S = B)$

$p_1 = P(CA = 1|SL = 1)$

$p_2 = P(CA = 1|SL = 0)$

P() denotes the probability of the event shown in the bracket; θ is the actual quality of firms, which is not observable to investors or rating agencies but only to firms themselves. τ_1, τ_2 indicate the firms' decision of whether to solicit the rating services. p_1 p_2 show the rating agencies' decision of whether to give lower ratings to the rated firm according to the solicitation status. All the five probabilities are always larger than zero and smaller than one.

To justify the decisions of rating agencies who issue lower ratings for unsoliciting firms (p_1 >p_2), firstly, I stand on the position of rating agencies to infer the actual firm quality according to the solicitation status (for convenience I assume that only the information of solicitation status can be obtained by rating agencies).

The aim of credit agencies in this model is to infer the actual probability of the firm to be good or bad based on the observation of firms' solicitation. Specifically, rating agencies observe the solicitation status (SL) as either G or B. If the observation is SL=1, rating agencies have the information of conditional probability of S=G as $P(\mathrm{S}=\mathrm{G}|\mathrm{SL}=1)=\frac{P(S=G,SL=1)}{P(S=G,SL=1)+P(S=B,SL=1)}=\frac{\theta\tau_1}{\theta\tau_1+(1-\theta)\tau_2}$.

The difference between the conditional probability and unconditional probability with no observation of solicitation status is:

$$P(\mathrm{S}=\mathrm{G}|\mathrm{SL}=1)-P(S=G)=\frac{\theta\tau_1}{\theta\tau_1+(1-\theta)\tau_2}-\theta=\frac{\theta(1-\theta)(\tau_1-\tau_2)}{\theta\tau_1+(1-\theta)\tau_2} \qquad (4.2.1)$$

If the observation is SL=0, rating agencies have the information of conditional probability of S=B as $P(S=\mathrm{B}|\mathrm{SL}=0)=\frac{P(S=B,SL=0)}{P(S=B,SL=0)+P(S=G,SL=0)}=\frac{(1-\theta)(1-\tau_2)}{(1-\theta)(1-\tau_2)+\theta(1-\tau_1)}$.

The difference between the conditional probability and unconditional probability with no observation of solicitation status is:

$$P(\mathrm{S}=\mathrm{B}|\mathrm{SL}=0)-P(S=B)=\frac{(1-\theta)(1-\tau_2)}{(1-\theta)(1-\tau_2)+\theta(1-\tau_1)}-(1-\theta)$$

$$=\frac{\theta(1-\theta)(\tau_1-\tau_2)}{(1-\theta)(1-\tau_2)+\theta(1-\tau_1)} \qquad (4.2.2)$$

Exploring Equations (4.2.1) and (4.2.2), I find that denominators in both algebraic fractions are always positive and hence the signs of them depend on those of numerators. For numerators, the fraction $\theta(1-\theta)$ is always positive. Therefore, the signs of both results in Equations (4.2.1) and (4.2.2) depend on the sign of $(\tau_1-\tau_2)$.

Now I introduce the mathematical expression of self-selection of rated firms:

$$\tau_1 > \tau_2 \qquad (4.2.3)$$

Equation (4.2.3) describes the selection bias: good firms are more likely to solicit the rating services than bad firms.

Under the condition of (4.2.3), the mathematical results of (4.2.1) and (4.2.2) are always positive:

$$P(\mathrm{S} = \mathrm{G}|\mathrm{SL} = 1) - P(S = G) > 0 \qquad (4.2.4)$$

$$P(\mathrm{S} = \mathrm{B}|\mathrm{SL} = 0) - P(S = B) > 0 \qquad (4.2.5).$$

Equation (4.2.4) shows that if rating agencies observe that the firm *requests* solicited ratings, the probability of it to be a *good* firm is larger than when no information of solicitation status is obtained. Equation (4.2.5) shows that if rating agencies observe that the firm *does not request* solicited ratings, the probability of it to be a *bad* firm is larger than when no information of solicitation status is obtained. Therefore, it is a rational decision for rating agencies to rate higher for solicited rating recipients and rate lower for unsolicited rating recipients, which can be expressed as

$$p_1 > p_2 \qquad (4.2.6)$$

In terms of the degree of p_1 and p_2, technically speaking, if we assume that the credit rating agency has knowledge of the parameters θ, τ_1 and τ_2, the technical assumption of a agency to adjust the p_1 and p_2 is

$$\frac{p_1}{p_2} = \frac{\tau_1[\theta(1-\tau_1)+(1-\theta)(1-\tau_2)]}{(1-\tau_1)[\tau_1\theta+\tau_2(1-\theta)]} \quad (4.2.7)$$

(The inference of this technical assumption is presented in Appendix 4-1.1).

Equation (4.2.7) demonstrates the rationality assumption (a technical assumption) of the CRA: the CRA is able to adjust the ratio of probabilities of giving high ratings to recipients between solicited and unsolicited ratings. It is easy to prove that $\frac{p_1}{p_2}$ is always larger than 1 (p_1 is always larger than p_2): if I subtract the denominator from the numerator, I get the difference as

$$\tau_1[\theta(1-\tau_1)+(1-\theta)(1-\tau_2)]-(1-\tau_1)[\tau_1\theta+\tau_2(1-\theta)]$$

$$=(\tau_1-\tau_2)(1-\theta) \quad (4.2.8)$$

Recall that $(\tau_1-\tau_2)>0$ (the assumption of self-selection and θ is always less than 1, so Equation 4.2.8 is positive, which means that Equation 4.2.7 is larger than 1).

The next assumption I introduce here is the non-bias assumption of the CRA: the CRA does not have different attitudes towards the solicited and unsolicited rating recipients. In other words, given the actual condition of the rated firm (S=G or B), the opinion given by the CRA is not relevant to the solicitation status.

$$P(CA=1|S=G,SL=1)=P(CA=1|S=G,SL=0) \quad (4.2.9)$$

$$P(CA=1|S=B,SL=1)=P(CA=1|S=B,SL=0) \quad (4.2.10)$$

Under the condition of CRA's rationality (4.2.7) and fairness (4.2.9 and 4.2.10), I measure the information provided by the CRA to the market (the investors) by calculating the conditional probability of the firm status given the credit rating agencies' opinion (CA) as well as the solicitation status (SL):

$$P(S=G|SL=1,CA=1)=\frac{P(S=G)P(SL=1|S=G)P(CA=1|S=G,SL=1)}{P(SL=1)P(CA=1|SL=1)}$$

$$P(S=G|SL=0,CA=1)=\frac{P(S=G)P(SL=0|S=G)P(CA=1|S=G,SL=0)}{P(SL=0)P(CA=1|SL=0)}$$

(The inference of these two equations is also shown in Appendix 4-1.1)

Given the rationality assumption (4.2.7) and the non-biased assumption (4.2.9 and 4.2.10), I get the conclusion that

$$P(S=G|SL=1,CA=1)=P(S=G|SL=0,CA=1) \quad (4.2.11)$$

Equation 4.2.11 shows that the information given by the CRA's opinion regarding the status of the rated firms is not related to the solicitation status: the conditional probability that the firm is 'Good' is the same whether SL=1 or 0.

I further test whether the CRA's opinion (CA) is informative by calculating the difference between the conditional probability of being good and the unconditional probability. I measure the rating quality by examining whether ratings provide extra information to investors who do not take solicitation status into consideration (un-informed investors). Un-informed investors do not realize the factor of solicitation status but only observe the rating opinion (CA=1 or 0) given by rating agencies. Their aim is also to infer the probability of the firm to be good/bad.

$$\mathrm{P}(S=\mathrm{G}|\mathrm{CA}=1)-P(S=G)=\frac{\theta(1-\theta)(p_1-p_2)(\tau_1-\tau_2)}{\theta\tau_1p_1+\theta(1-\tau_1)p_2+(1-\theta)\tau_2p_1+(1-\theta)(1-\tau_2)p_2} \quad (4.2.12)$$

(The inference of this equation is shown in Appendix 4-1.2)

I find that denominators in both algebraic fractions are always positive and hence the signs of these depend on those of numerators. For numerators, the fraction $\theta(1-\theta)$ is always positive. Therefore, the signs of both results in Equations (4.2.7) and (4.2.8) depend on the sign of $(p_1-p_2)(\tau_1-\tau_2)$.

According to the assumption stated in (4.2.3) which reflects the self-selection of firms, we know that $(\tau_1-\tau_2)>0$. Furthermore, according to the rational rating agency assumption obtained in (4.2.7), we know that $(p_1-p_2)>0$. Therefore, under the condition of (4.2.3) and (4.2.6), we get

$$P(S=\mathrm{G}|\mathrm{CA}=1)-P(S=G)>0 \qquad (4.2.13)$$

(4.2.13) states that the signal of *positive* rating given by rating agencies provides extra information for investors by showing a *higher probability of the firm to be good* than where no rating information is provided. In other words, the rating is informative for the investors.

Taking the conclusions drawn in (4.2.11) and (4.2.13) into consideration together, I find a theoretical background to state that if the CRA is rational and un-biased, the quality of its ratings in terms of the predictability of firms' status is not related to the solicitation status and the ratings are informative to the investors.

In summary, I obtain three essential conclusions in this theoretical discussion:

Conclusion 1: The CRA is reasonable to rate lower for unsolicited rating recipients if the self-selection assumption holds (Equation 4.2.6). This conclusion is empirically tested in Section 4.5.1.

Conclusion 2: The predictability of ratings is the same regardless of the solicitation status (Equation 4.2.11).

Conclusion 3: The ratings are informative to the market by giving extra information about the rated firms (Equations 4.2.13).

Conclusions 2 and 3 are tested in Section 4.5.2. In order to have empirically testable statements, I use the default risk, measured by DTD (Distant to Default) as an indicator of firm status and use rating change timeliness as an indicator of the rating information degree.

4.3.2 Hypotheses

For empirical tests, I raise two sub-hypotheses as follows.

Hypothesis 4-1: Rating level hypothesis: the ratings provided by Moody's are lower if they are issued as unsolicited ones;

Hypothesis 4-2: Rating quality hypothesis: the rating of Moody's is informative regarding the future default risk of the rated firms and the rating quality is not significantly different between solicited and unsolicited ratings.

The rest part of this paper is to empirically test these two hypotheses using historical records of Moody's ratings for sample firms.

For Hypothesis 4-2, an essential factor is the measure of the rating quality. Rating quality has been widely discussed in terms of its empirical measurement, including the default risk predictability of ratings (Becker and Milbourn, 2011; Baghai and Becker, 2018) and rating change timeliness measures (Bannier et al., 2009; Berwart et al., 2016).

Default predictability is the key indicator of assessing the rating quality because the most important role that a credit rating should play is to inform the rated firm's risk of default to market participants. The absence of gaps of default risk predictability between unsolicited and solicited ratings implies that given the same level of ratings, the ex-post measures of default risk are not significantly different, regardless of the solicitation status. Thus, the lower ex-ante unsolicited ratings are reasonable. Firms with weak characteristics opt not to purchase the rating services from Moody's and rating agencies identify those firms with weaker performance estimates to offer unsolicited ratings to. Moody's estimates are accurate, reflected by a weaker ex-post firm performance who received unsolicited ratings.

Besides predictability of default, the speed of ratings is another measure of rating quality (Cheng and Neamtiu, 2009) because it indicates the CRAs' ability to capture the variation of rated firms' fundamentals and mirrors the information contents of the rating actions. The absence of gaps of rating action timeliness for solicited and unsolicited ratings implies that although unsolicited ratings are lower, the speed of Moody's revising them is not impacted by the solicitation status.

In summary, the self-selection hypothesis can be empirically tested by examining the rating quality gap, which is measured by the ratings' predictability and the rating action speed (timeliness). The absence of a weaker rating quality for unsolicited ratings shows evidence for self-selection hypothesis. It indicates that; 1) the lack of internal information does not undermine the rating quality of unsolicited ratings, 2) the fact that no fee is paid by issuers does not motivate rating agencies to offer poorer-quality ratings for unsolicited ratings and, 3) the criteria of rating agencies to assign ratings are not related to the status of solicitation. By these three conclusions, I may exclude the hypothesis of strategic behavior of CRAs, which means that I am not able to find evidence to show that CRAs, for whatever reason, strategically under-rate firms who do not pay them.

The finding of self-selection motivation of Moody's is favorable for their reputation because it fits the aim officially stated by Moody's of issuing unsolicited ratings, 'increasing the market transparency'. Rating agencies recognize those weak firms with potential risks which are not yet acknowledged by general investors and issue ratings of these 'risky' firms to investors, despite their not collecting any service fees from rated firms, in order to maintain the market transparency. Moreover, the relatively lower ratings provide extra information to the market by releasing a signal to investors that those rated firms are more likely to perform worse than their solicited peers.

4.4 Data

The data source of historical rating information, fundamental information as well as the market-based information is the Bloomberg database. The sample period starts in 2010 when the record of Moody's unsolicited ratings started to be disclosed in Moody's online reports and ends in the year 2017 when I started to conduct this study.

4.4.1 Identification of treatment and control sample firms

The key portion of ratings analyzed in this paper is the unsolicited rating. The research is conducted centered on Moody's ratings and supplemented by those of S&P and Fitch. Therefore, the initial sample (treatment group) consists of firms who do not purchase rating services and receive unsolicited ratings from Moody's. The identification of treatment group firms is based on the reports of unsolicited ratings which are released quarterly from 2010 (the earliest information available on Moody's website) till 2017. Those unsolicited companies are filtered according to the following criteria.

--deleting companies not listed on the stock market

--deleting companies with a very small (<2 years) age

--deleting companies without fundamental information in Bloomberg.

After the filter, I have 40 companies with unsolicited ratings offered by Moody's in the sample. 26 of the sample firms are located in the European region and the remaining are located in Asia. The majority of the 40 firms (31) are in the banking sector and the remaining firms are in other sectors.

The supplemental sample (control group) consists of firms who purchase rating services and receive solicited ratings from Moody's. In order to only consider the factor of solicitation status and avoid the contamination of firms' fundamental factors (region, sector, and size), some initial criteria should be used to select control firms for each of the 40 treatment group firms. The criteria are: 1) the control firms receive ratings from Moody's with their solicitations; 2) the control firms are listed on the stock market and have valid historical stock prices in the sample period; 3) the control firms are classified in the same category (sector) as the treatment firm; 4) the control firms are located in the same region (Europe or Asia) as the treatment firm and 5) the market capitalization (size) ranking of the control firm in the corresponding region is close to that of the treatment firm (the ranking difference is not larger than 20).

By the criteria above, a total of 167 control firms are selected[15]. The sector and region distribution of the treatment group and the control group is shown in Table 4-1.

Table 4-1 Region distribution and sector distribution of treatment and control groups

	Treatment Group	**Control Group**
Region		
Europe	26	128
Non-Europe	14	40
Sector		
Banking/Finance Sector	31	102
Others	9	64

[15] Some of the firms play the role as the control firms for more than one treatment firm.

The number of selected firms in the control group is higher than that of firms in the treatment group. This is consistent with the fact that Moody's only issues a very small proportion of unsolicited ratings. The region and sector distributions of control group firms are more balanced than those of treatment group firms (treatment group firms are concentrated in the European region and in the banking/finance sector).

Even though I use the criteria of region, sector and firm size to initially filter the control group firms, such rough filter procedure does not capture the factors of other accounting-based fundamentals, such as leverage, profitability, etc. The comparison of rating levels without controlling those factors may create biased results. Therefore, matching procedures, based on the fundamental variables, should be conducted before the comparison of rating levels.

4.4.2 Fundamentals

Accounting-based fundamental information of the treatment group firms and control group firms is collected and applied in the procedure of matching and regressions in order to compare the levels of unsolicited and solicited ratings issued for firms with similar characteristics.

Considering the data access of Bloomberg and the categories of information (size, leverage, profitability) which is generally considered by the market to assess the quality of firms, I select eight accounting indicators (shown in Table 4-2) to be used in further analyses as control fundamentals.

Table 4-2 Description of fundamental accounting-based variables

Category	Variable	Description
Size	Total Assets	Total amount of the firm's assets, by USD
Leverage	Total Debt to Total Asset	Total amount of debt relative to assets: The higher the ratio, the higher the degree of leverage and corresponding financial risks.
	Degree of Financial Leverage	Percentage change in earnings per share over the percentage change in EBIT
Profitability	Return on Assets	Net Income / Total Assets
	Growth Rate of Assets (Quarterly)	The ratio between assets in the current quarter and Assets in the previous quarter minus 1
	Total Investment to Total Assets	The ratio between total investment assets and total assets
	Asset Turnover	The ratio between net sales revenues and average total assets
	Ratio: Sales to Total Assets	The ratio between the sales to the total assets

All accounting data are collected on a quarterly basis. Excluding the missing values, I obtain 2315 observations of the firm-quarter pair of fundamental variables for unsolicited rating recipients (treatment group) and 7830 observations for the solicited rating recipients (control group). The descriptive statistics of these variables is shown in Appendix 4-2.

4.4.3 Matching Scheme (Propensity Score Matching)

Due to the imbalanced data between the treatment group (40 firms) and the control group (167 firms) as well as the fact that initial filter of control group firms does not consider other accounting-based variables than firm size, I apply the method of Propensity Score Matching (PSM) for each of the treatment group firms to select its 'matched control firms' from the control group. For matching algorithms, normally there are two methods: caliper matching (a maximum allowable distance between propensity scores is specified) and nearest neighbor matching (matches each treatment group participant with the closest possible untreated group participant). The matching mechanism I selected in this chapter is the ‘nearest neighbor with replacement’. The reason that I do not use another matching method is that the objective is to match each of the banks treatment group with fixed number of banks (2, 3 and 4) from the control group. Therefore, using caliper matching may cause a problem that different treatment group banks have different numbers of control group counterparties.

The procedure is in two steps:

1) I run logit regression for all firms: regress the dummy variable indicating whether the firm’s rating by Moody’s is unsolicited (=1) or solicited (=0), on fundamental variables and region, sector dummies. Using the estimated coefficients and information of fundamentals, I calculate a score for each of the sample firms. The score indicates the probability of the firm to be categorized as ‘unsolicited’.

2) For each of the treatment group firms, I select N firms who have the closest scores with it, from the control group. Each control group firm is allowed to be picked more than once for more than one treatment group. N is taken as 2, 3 and 4 respectively to have the flexible ratios between the treatment group sample and the matched control sample. The distance of fundamental characteristics between treatment firms and selected control firms is larger if the selection of N is larger because by taking a larger N I allow more control firms to be selected for each of the treatment firms. The numbers of firms and firm-quarter observations of the treatment group and the control group for different N are shown in Table 4-3. In all the further analysis shown in Section 5, I use four matching schemes to compare the situation for unsolicited and solicited cases: three schemes use N from 2 to 4 to select control firms respectively and the fourth scheme use all control firms as members in the control group.

Table 4-3 Numbers of firms and firm-quarter observations for different PSM matching schemes

N (the number of nearest neighbors in the PSM matching)	No. of Firms		No. of Firm-Quarter Obs	
	Treatment Group	Control Group	Treatment Group	Control Group
2	40	58	2315	2811
3	40	72	2315	3521
4	40	87	2315	4712

4.4.4 Distance to Default

To measure the default risk predictability of Moody's ratings, I need to measure the default risks of firms in the treatment and control groups. Some previous studies use actual default events of firms and the relationship between default events and credit ratings to reflect the predictability (Becker and Milbourn, 2011; Baghai and Becker, 2018). However, the actual rating events in my sample are rare. Therefore, I used an indicator of Distance to Default (DTD) (Merton, 1974) to measure the default risk of sample firms quarterly. In empirical tests, DTD is a very commonly-used tool to proxy the credit risk (i.e. probability of default) of firms (Yu, 2005; Blundell-Wignall & Roulet, 2013; Milne, 2014).

DTD is calculated as:

$$\frac{\ln\left(\frac{V}{F}\right) + (r - 0.5\sigma_V{}^2)/T}{\sigma_V\sqrt{T}} \qquad (4.4.1),$$

where V: market value of the firm asset; F: book value of the firm debt, which is equal to the sum of short-term debt and half of the long-term debt; r: risk-free interest rate; σ_V: volatility of V and T: time horizon.

V and σ_V are unobservable and obtained by solving the functions shown in Formula (4.4.2) and Formula (4.4.3).

$E=VN(d_1)-e^{-rT}FN(d_2)$ (4.4.2)

$\sigma_E=(V/E)N(d_1)\sigma_V$ (4.4.3), where $d_1=\frac{\ln\left(\frac{V}{F}\right)+(r+0.5\sigma_V{}^2)/T}{\sigma_V\sqrt{T}}$ and $d_2= d_1-\sigma_V\sqrt{T}$.

In Equation (4.4.3), *E* is the market value of the firm equity; σ_E is the volatility of E; N() indicates the normal distribution function.

Other components are observable:

E=stock price × outstanding share (daily); F=current debt+0.5× long-term debt (quarterly); σ_E=yearly standard deviation of E; r=3-month treasury bill rate (collected from Bloomberg) and T=0.25 (a quarter is 0.25 year).

To solve V and σ_V I use the iterated estimation method by repeatedly setting estimates as new observations and solving the equations until the differences between newly-solved estimates and previously-solved estimates are lower than 0.001.

A higher DTD indicates a lower risk of default. According to Formula (4.4.1), the higher DTD (lower risk) may be derived from one or more factors as follows: a higher entity value (V), a lower debt value (F), a higher risk-free rate in the market (r) and a lower volatility of entity value (σ_V).

4.5 Methodology and Results

The empirical analysis is conducted into two parts in order to test the conditions for the two sides of the self-selection hypothesis. One part is aimed at examining Hypothesis 4-1: unsolicited ratings are more conservative than solicited ones issued by Moody's. The other part is aimed at testing Hypothesis 4-2 by comparing the rating quality between unsolicited and solicited ratings.

4.5.1 Test of Rating Levels between Moody's Unsolicited and Solicited Ratings

To test whether unsolicited ratings are systemically more conservative than solicited ones, I conduct the comparison into two streams: single-agency comparison and multi-agency comparison. For the single-agency test, unsolicited and solicited ratings issued by Moody's are considered and the average rating-level gaps between those two types of ratings are identified and tested. Such single-agency tests are widely conducted by the literature (for example, Byoun and Shin (2002), Poon et al. (2009)) to demonstrate the rating gaps of unsolicited and solicited ratings. To exclude the possibility that the seemingly lower levels of unsolicited ratings are due to the systematically weaker observable characteristics of unsolicited rating recipients but not the reaction of Moody's to self-selection behavior (unobservable factor) of rated firms, I use logit regressions to control the fundamentals. To further improve the feasibility of the results, I supplement the single-agency test by conducting a multi-agency test. The gap of ratings among different big CRAs have been widely used to study the rating industry. For example, Livingston et al. (2008) apply the rating gaps as an indicator of rating migration. Alsakka and ap Gwilym (2010-a) extended the study to the sovereign rating area and study the split sovereign ratings as a factor of future rating variations. Vu, H et al. (2017) use the sovereign rating splits to reflect the political risks and the transparency of the sovereigns. In this chapter, by a difference-in-difference analysis, I consider the relative rating gap between Moody's and the other two agencies (S&P and Fitch) to test whether the gap varies if the Moody's rating is unsolicited or not. The inherent assumption is that although the absolute rating levels of different CRAs may not be the same, their gap should be the same conditional on the same solicitation status. Therefore, the D-i-D estimators which show the difference of rating gaps for the solicited rating cases and the unsolicited rating cases indicate the effect of solicitation status on the rating conservatism.

I bear in mind that the test in this section is an empirical reflection of the conclusion drawn in the theoretical model (Formula 4.2.6) which shows that under the condition of self-selection, it is the accurate decision for rating agencies to rate lower for the firms who do not request the solicited rating services. The empirical finding supports the results of the theoretical model in Section 4.3.1. Both the empirical and theoretical analyses show that it is not a biased behavior for CRAs to offer lower ratings for firms who do not solicit the rating services.

4.5.1.1 Numeric transformation of rating notches

In order to quantitatively analyze the ratings, I follow the rule used by Ashcraft et al. (2011) and transform the original letter-format rating indicators into numerical indicators, from 1, which indicates the highest rating level, to 21, which indicates the lowest rating level. Details of the transformation are shown in Table 4-4.

The letter-format rating indicator system used by Moody's is different from that used by S&P and Fitch. But the total number of rating notches (21) are the same among the three agencies. After the transformation, I can not only take the mathematical calculation (t-test and logit regression) on Moody's rating levels but also quantitatively compare the rating levels of different rating indicating systems used by different rating agencies.

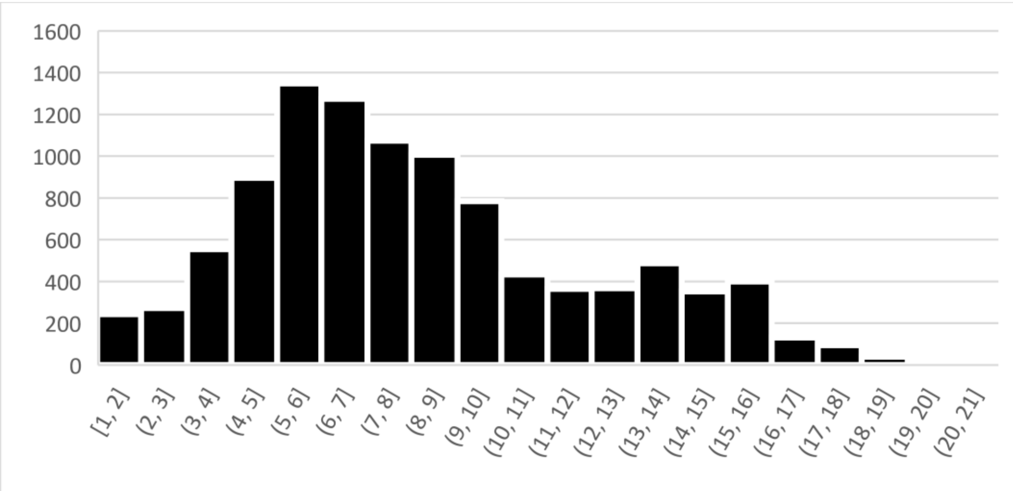
The frequency distribution of quarterly rating indicators of all the sample firms is shown in Figure 4-1. The shape of the figure implies that the distribution of rating levels is positively skewed. The majority of the historical ratings concentrate in the range of [5,10], which represents the range between Aa1 and Baa3. It is reasonable because the firms with ratings higher than Aa1 are regarded as 'top-rated' ones who have superior features and firms with ratings lower than Baa3 are regarded as 'non-investment grade' ones who may encounter regulatory restrictions by regulators. The firms rated between those two ranges represent moderate ones and take the biggest proportion.

Table 4-4 Rating indicator transformation

Rating notch (Moody's)	Rating notch (S&P and Fitch)	Value of number-format variable
Aaa	AAA	1
Aa1	AA+	2
Aa2	AA	3
Aa3	AA-	4
A1	A+	5
A2	A	6
A3	A-	7
Baa1	BBB+	8
Baa2	BBB	9
Baa3	BBB-	10
Ba1	BB+	11
Ba2	BB	12
Ba3	BB-	13
B1	B+	14
B2	B	15
B3	B-	16
Caa1	CCC+	17
Caa2	CCC	18
Caa3	CCC-	19
Ca	CC	20
C	C	21

Figure 4-1 Frequency of Quarterly Rating Notches of the data sample

This figure represents the frequency distribution of quarterly numerical rating indicators of sample firms. The rating notches are numerically transformed into the integral format according to the rule that a higher rating is transformed into a lower integer value (transformation details are shown in the Table 4-4).



4.5.1.2 Single-Agency Comparison

The single-agency comparison is only focused on the ratings of sample firms issued by Moody's. A univariate test (will be discussed later) directly compares the numerically transformed rating indicators of the treatment group firms (unsolicited) with those of control group (solicited) and a trend of lower ratings (reflected by a higher value of transformed rating indicators) of treatment group firms are observed. However, this finding is vulnerable because it does not take the current fundamentals of the sample firms into account. The lower ratings of treatment firms may be reflecting a weaker current fundamental of those firms but not the self-selection behaviors of Moody's who forecasts that the selected unsolicited firms have weaker future performances. Therefore, a multi-variate test should be conducted as an essential supplementation. Specifically, I run logit regressions of the rating indicators on the key variable of solicitation status along with fundamental variables and find a significant estimate on the solicitation status variable, which indicates that after controlling current fundamentals, the solicitation status of Moody's ratings is associated with the level of ratings given by it.

Univariate test

The univariate test is the most intuitive way to compare the rating levels between unsolicited and solicited ratings by Moody's, without considering any other fundamental information of sample firms but ratings. The principle is to directly compare the average levels of these two types of ratings and calculate the mean and standard deviations of the level gap to obtain the t-statistics of the gap. In the analysis process, I use the logarithm of the numerical rating indicator to replace the original integer-format one to eliminate the potential negative impact of the distribution's skewness on the feasibility of the t-test. I use the quarterly firm-rating pairs to construct the dataset for the univariate test. Firms in both the treatment group (unsolicited) and the control group (solicited) are selected and the different matching schemes based on the PSM method are applied respectively to compare the average value of numerically transformed rating indicators. The matching schemes vary according to the selection of N (N=2,3, and 4), which is the number of nearest neighbors selected from the control group for each of the treatment firms. The t-test result is shown in Table 4-5.

Table 4-5 T-test of the difference of average logarithm of ratings between treatment group (unsolicited ratings) and control group (solicited ratings)

The table shows the result of the t-test of the rating gaps between unsolicited ratings and solicited ratings. The rating notches are numerically transformed according to Table 4 and taken the format of logarithm. Four PSM matching schemes are applied according to different numbers of nearest neighbors in the PSM matching. Figures in the brackets demonstrate the t-statistics.

N (Number of nearest neighbors in the PSM matching)	2	3	4	All
No. of Observations in treatment/control groups	2315/2811	2315/3521	2315/4712	2315/7830
Average log rating of Treatment Group (Unsolicited)	2.149	2.149	2.149	2.149
Average log rating of Control Group (Solicited)	2.062	2.053	2.055	2.032
Difference (treatment - control)	0.087*** (6.79)	0.096*** (7.73)	0.093*** (7.90)	0.116*** (10.77)
*** 1% significance level; ** 5% significance level; *10% significance level				

For all the four matching schemes, I find a larger average value of the logarithm of rating indicators of unsolicited ratings than solicited ratings. The transformation details presented in Table 4-4 show that a higher value of rating indicators is equivalent to a lower (more negative) rating level. Therefore, the average unsolicited ratings issued by Moody's are lower (more negative) than solicited ratings. After taking the exponent (the reverse of the logarithm) of the figures in the table, I find that the average level of unsolicited ratings (exp{2.149}=8.576) is equivalent to the middle point between Baa1 (8) and Baa2 (9). The average level of solicited ratings depend on the selection of matching schemes but all the four figures are close to exp{2.05}=7.768 (equivalent to the middle point between A3 (7) and Baa1 (8)). From an intuitive perspective, the average level of unsolicited ratings is 1 notch lower than solicited ratings. The t-test result shows that the rating difference between those two unsolicited ratings are statistically significant at the 1% significance level.

Besides, the observation of for different PSM matching criteria shows that with the PSM matching, the level of difference is lower than if there is no matching and with the rise of the number of matched counterparties, the difference is getting wider. It shows that the use of PSM matching is associated with a reduction of bias. Similar observations can be found for the following tests (shown in Tables 4-6 and 4-8).

The results in Table 4-5 provide a preliminary evidence of a lower unsolicited rating. However, fundamental variables and other fixed effects (year, quarter, country and sector) are not considered in this analysis. Therefore, I run the ordered logit regression to control those factors.

Regression Test

I use ordered logit regression to compare the rating levels between unsolicited and solicited ratings controlling fundamental factors of the firms:

$$R^*{}_i = \beta_{4-1,1} Unsolicited\_Dummy_i + \boldsymbol{\gamma X'} + \varepsilon_i \qquad (4.5.1)$$

The regression is run on the basis of quarterly firm-rating pairs and each *i* represents a pair. The dependent variable, $R^*{}_i$ represents the unobservable latent variable which defines the thresholds of various alternatives of credit rating levels R_i, which are described in Table 4-4. A higher R_i represents a lower (more negative) rating. The key independent variable on the right side of Equation (4.5.1) is $Unsolicited\_Dummy_i$, which is equal to 1 if the rating of pair *i* is unsolicited and 0 if the rating is solicited.

$\beta_{4-1,1}$, the corresponding estimates on the dummy variable, captures the impact of solicitation status on the rating level. To fit the hypothesis of self-selection, I expect a significant positive $\beta_{4-1,1}$ which means that if the ratings are unsolicited ($Unsolicited\_Dummy_i = 1$), the rating level should be lower (a higher R_i and a higher $R^*{}_i$). $\boldsymbol{X'}$ represents a vector containing eight fundamental variables shown in Table 4-2 as well as the dummy variables defining the year, quarter, country and sector of the pair *i*. $\boldsymbol{\gamma}$ is the corresponding estimates on the sector $\boldsymbol{X'}$.

The variables contained in the vector $\boldsymbol{X'}$ help the model (4.5.1) to eliminate the fundamental variables and other fixed effects in the analysis of solicitation status's impact on the rating levels. $\beta_{4-1,1}$ captures the association between solicitation status and rating levels assuming that the firms who receive corresponding ratings issued by Moody's have the same level of fundamentals are issued in the same year and same quarter, are located in the same country and are run in the same sector.

For Equation (4.5.1), I assume that the decisions of providing unsolicited ratings for selected firms made by CRAs is not related to the current status of control variables in $\boldsymbol{X}'$ but are only based on the forecast of the firms' quality. I acknowledge that this is a very strong assumption and the violation of this assumption may cause an endogeneity problem. To tackle this problem, I use the multi-agency comparison (difference-in-difference method) to eliminate the possibility of biased selection of providing unsolicited ratings (see 4.5.1.3).

The empirical result of Equation (4.5.1) is shown in Table 4-6. As expected, regardless of the matching schemes, the estimates on unsolicited dummy $\beta_{4-1,1}$ are always significantly positive. The mathematical intuition is that after controlling the fundamentals and other fixed effects, if the rating is unsolicited, the rating notch has a higher probability of being mapped to a high value of $R^*{}_i$ which is defined as the threshold of lower (more negative) rating levels. In a word, the status of unsolicited ratings is associated with a lower rating level.

This finding enhances the result of the univariate test by controlling other fundamental factors ($\boldsymbol{X}'$). If I investigate the estimates on those fundamental factors, I find that the selected accounting-based fundamentals have a significant association with the rating levels issued by Moody's. It suggests that Moody's may consider those factors when determining which rating notches it would give to the rated firms. Specifically, estimates on *Total_Debt_to_Total_Asset* and *Degree_of_Financial_Leverage* are positive which indicates that Moody's might see debt ratio as a negative factor for the firm. This is natural and reasonable because a higher level of debt ratio (or leverage) is associated with a higher risk of the firms to default on the debt. Estimates on *Total_Investment_to_Total Assets* are also positive. It indicates that Moody's have conservative attitudes to the expansion of firms' investment scale and regard it as a negative indicator of the future default risk. Estimates on *Sales_to_Assets, Return_on_Assets* and *Asset_Growth_Rate* are negative which means that those factors may be viewed by Moody's as positive indicators of the firm's default risk. Moody's ratings are higher if the rated firm has a larger current value of sales ratio, ROA and asset growth ratio. Besides that, Moody's rating is not associated with the size of the firms (insignificant estimates on *Total_Asset*). It reflects the effect of the initial filter of the control sample firms, with the criterion 'the market capitalization (size) ranking of the control firm in the corresponding region is close to that of the treatment firm (the ranking difference is not larger than 20)'. Therefore, the treatment (unsolicited) group and control (solicited) group should contain firms with similar sizes so the statistical estimates on the firm size are not significant.

Supplemental test: rating stability

So far I have shown evidence of lower rating levels of unsolicited ratings. However, whether the rating levels of unsolicited and solicited ratings have a different pattern of rating changes is not studied. In other words, in this section I will investigate whether the gap between those two types of ratings is stable in time and whether one type of rating is more likely to be changed by Moody's than another type.

Table 4-6 Ordered Logistics Regression of rating notches on unsolicited rating dummy

This table shows the result of ordered logit regression. The regression is run on the basis of quarterly firm-rating pairs. Sample firms are the recipients of both unsolicited and solicited firms. Four matching schemes are applied to select the control group firms with different number of nearest neighbors. The dependent variable is the unobservable variable defining the thresholds of numerically transformed rating-notch indicators. A higher value of the dependent variable is equivalent to a lower (more negative) actual rating (details of the transformation are shown in Table 4-4). The key independent variable is the unsolicited dummy which is equal to 1 if the corresponding rating is unsolicited and 0 if it is solicited. Fundamental variables are described in Table 4-2. Year, quarter, country and sector are controlled. The estimation is by MLE method. Figures in the brackets are corresponding Wald-statistics.

*** 1% significance level; ** 5% significance level; * 10% significance level

	Matching Scheme			
Number of nearest neighbors in the PSM matching	2	3	4	All
Estimates				
Unsolicited Dummy	**0.162*** (7.57)**	**0.209*** (13.52)**	**0.377*** (47.50)**	**0.215*** (18.21)**
Total Asset[a]	4.97 (0.51)	6.68 (1.01)	11.31** (4.65)	-14.8 (116.14)
Total Debt to Total Asset	0.021*** (86.85)	0.021*** (94.76)	0.020*** (101.20)	0.020*** (199.16)
Degree of Financial Leverage	0.019*** (20.48)	0.018*** (21.12)	-0.00005 (0.012)	-0.00002 (0.016)
Return on Assets	-0.032*** (9.01)	-0.031*** (11.50)	-0.029*** (11.84)	-0.0352*** (35.38)
Growth Rate of Assets (Quarterly)	-0.0014 (0.84)	-0.0027* (3.68)	-0.0033*** (11.89)	-0.0033*** (21.14)
Total Investment to Total Assets	0.0040*** (10.93)	0.0068*** (32.82)	0.00084*** (67.29)	0.0075*** (94.11)
Asset Turnover	1.118** (4.43)	1.400*** (7.78)	0.605 (1.88)	1.122*** (20.51)
Ratio: Sales to Total Assets	-1.719 (0.67)	-2.03 (0.27)	0.396 (0.051)	-1.578* (2.82)
Year Control	Yes	Yes	Yes	Yes
Quarter Control	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes
Sector Control	Yes	Yes	Yes	Yes
N	3912	4443	5131	8595
AIC	20285.446	22892.729	26201.431	44150.040
SIC	20599.036	23212.684	26528.584	44502.987
-2Log	20185.446	22792.729	26101.431	44050.040

a: the unit of the estimates is $\times 10^{-6}$

The ordered logit regression is also applied to study this issue. The regression model is shown in Equation (4.5.2). What distinguishes the test in this equation from that in Equation (4.5.1) is the set of dependent variables. In Equation (4.5.1) ${R^*}_i$ refers to the latent variable linked to the level of ratings while in Equation (4.5.2) ${RC^*}_i$ refers to the latent variable linked to the quarterly change of rating levels (*RC* is short for 'rating change'). The change of rating level is measured as the absolute value of the gap between the numerically-transformed rating level in the current quarter minus that in the previous quarter. Correspondingly, fundamental variables in the vector $\boldsymbol{X}'$ are adjusted to the format of quarterly change rather than the absolute values. Besides that, I split the cases of rating change into 'upgrade' cases and 'downgrade' cases and regressions are run separately for either of the two cases.

$$RC^*{}_i = \beta_{2,1} Unsolicited\_Dummy_i + \boldsymbol{X}'\boldsymbol{\gamma} + \varepsilon_i \qquad (4.5.2)$$

Regression results are shown in Table 4-7.

Table 4-7 Ordered Logistics Regression of rating changes on unsolicited rating dummy

This table shows the result of ordered logit regression. The regression is run on the basis of quarterly firm-rating pairs. Sample firms are the recipients of both unsolicited and solicited firms. Four matching schemes are applied to select the control group firms with different number of nearest neighbors. The dependent variable is the unobservable variable defining the thresholds of quarterly change degree of numerically transformed rating-notch indicators. Numerical transformation detail is shown in Table 4-4. The quarterly change degree is measured by the absolute value of the gap between the rating in the current quarter minus the rating in the previous quarter. The key independent variable is the unsolicited dummy which is equal to 1 if the corresponding rating is unsolicited and 0 if it is solicited. Control variables are the quarterly change of fundamental variables described in Table 4-2. Year, quarter, country and sector are controlled. Upgrade and downgrade cases are analyzed separately. The estimation is by MLE method. Figures in the brackets are corresponding Wald-statistics.

	Matching Scheme							
Number of nearest neighbors in the PSM matching	2		3		4		All	
Up or Down	U	D	U	D	U	D	U	D
Estimates on Unsolicited Dummy	**-0.05 (0.057)**	**-0.16 (0.839)**	**0.01 (0.004)**	**-0.07 (0.189)**	**0.03 (0.021)**	**-0.06 (0.141)**	**-0.02 (0.020)**	**0.01 (0.005)**
Fundamental Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3260		3686		4212		6822	
AIC	929.553	1204.993	998.608	1326.882	1129.466	1531.626	1778.86	2453.40
SIC	1112.237	1387.677	1184.977	1513.251	1319.837	1721.996	1983.70	2658.24
-2Log	869.553	1144.993	938.608	1266.882	1069.466	1471.626	1718.86	2393.34

Estimates on the unsolicited dummy are insignificant in all cases. It implies that the solicitation status does not impact the probability of the firms to be upgraded or downgraded. Combining this finding with the result obtained for Equation (4.5.1), I conclude that the rating levels of unsolicited ratings are significantly lower than solicited ones and the degrees of variation pattern of both types of ratings are statistically the same in terms of the frequency and probability of rating changes. In summary, the lower level of unsolicited ratings is persistent and unlikely to be reversed because the upgrade and downgrade probabilities are not different for different solicitation statues.

4.5.1.3 Multi-Agency Comparison

In the logit regression analysis, I try to control the fundamental factors to exclude the possibility that the finding that unsolicited ratings are lower is derived from a systematically weaker firm characteristics of unsolicited rating recipients. In order to exclude all fundamental variables and only consider rating levels, I introduce the ratings given to the sample firms but issued by the other two big agencies, S&P and Fitch, to compare the relative level gap between Moody's and the other two's ratings. In principle, the variation of the rating level gap is not related to any fundamental information of rated firms but only related to the rating agency and the solicitation status.

The analysis is conducted in the way as follows. Moody's is regarded as the 'treatment agency' while either S&P or Fitch is selected as the 'control agency'. Those firms who receive ratings by both the treatment agency and the control agency are kept in the sample. After that, I filter out those firms who receive unsolicited ratings by the control agency to ensure that all the sample firms have only solicited ratings by the control agency and either solicited or unsolicited ratings by the treatment agency.

There are two layers of differences in the D-i-D analysis. The first layer is the average gap between numerically-transformed rating levels issued by the treatment and those issued by the control agency. This indicator reflects the gap of rating criterion applied by different rating agencies. The second layer of difference is the gap of first-layer difference between the firms who receive unsolicited Moody's ratings (treatment firms) and those who receive solicited Moody's ratings (control firms). The D-i-D estimator shows whether the rating criterion gap between Moody's and the other two agencies is associated with the solicitation status (Moody's) of the rated firms.

I use a hypothesized case as an example to show how the D-i-D estimates are established. In this example, the control agency is S&P. For those firms who receive unsolicited ratings by Moody's, the average rating by Moody's is *Baa* (corresponding transformed indicator, 9) and that by S&P is *A*- (corresponding transformed indicator, 7). The difference between Moody's and S&P ratings is 2 (equal to 9 minus 7). For those firms who receive solicited ratings by Moody's, the average rating by Moody's is A3 (7) and that by S&P is A (6). The difference between Moody's and S&P rating is 1 (equal to 7 minus 6). The numbers 2 (equal to 9 minus 7) and 1 (equal to 7 minus 6) represent the first-layer difference which is the rating criterion gap. Both of them are positive which means that Moody's ratings are more conservative than S&P because for the same rated firms, Moody's always issue lower ratings (a larger number is equivalent to a lower rating). If I compare the two numbers (2-1=1>0), I find that the D-i-D is positive. By the numbers I find evidence to show that, even though both agencies have certain degree of rating reduction (issue more negative ratings) for the treatment group firms, the positive D-i-D shows that Moody's degree of rating reduction is greater than S&P. It means that Moody's is more conservative than S&P towards the issuance of ratings for firms who do not solicit their rating service.

As shown in the hypothesized case, a positive D-i-D estimator is expected to enhance the hypothesis of self-selection. The positive estimator shows that compared to the control agency, Moody's issue more conservative ratings (reflected by a higher value of the transformed rating indicator) for unsolicited rating recipients.

The results of the multi-agency test are shown in Table 4-8.

The significance of D-i-D estimates is reflected by the t-statistics and the corresponding p- values.

For both the Moody's-S&P pair analysis and Moody's-Fitch pair analysis, I find significant evidence to show that Moody's issue more conservative ratings for its unsolicited rating recipients. D-i-D estimators are significantly positive, which fits my expectation: that compared to the control agency, Moody's issue more conservative ratings (reflected by a higher value of the transformed rating indicator) for unsolicited rating recipients.

Exploring the details on the D-i-D components, I find additional significant evidence. The treatment group firms have Moody's ratings at a lower level than S&P/Fitch ratings (reflected by positive values of the gap between Moody's ratings and S&P/Fitch ratings for treatment group). But the control group firms have Moody's ratings at a higher level than S&P/Fitch ratings (reflected by negative values of the gap between Moody's ratings and S&P/Fitch ratings for treatment group). It means that the solicitation status reverses the sign of relative gap between Moody's ratings and S&P/Fitch's ratings: if the firm solicits the rating service from Moody's, Moody's offer ratings at an average level higher than S&P/Fitch but if the firm does not solicit the rating service, Moody's offer ratings at an average level lower than S&P/Fitch. This provides evidence that Moody's ratings for unsolicited rating recipients are more conservative.

Table 4-8 Multi-agency test of rating levels

This table shows the result of multi-agency test. S&P and Fitch are respectively set as the control agency to compare the rating levels with Moody's. Treatment group firms are those who receive unsolicited ratings by Moody's but solicited ratings by the control agency. Control group firms are those who receive solicited ratings by both Moody's and the control agency. The selection of control group firms depends on the selection of matching scheme which requires different number of nearest neighbors to be collected in the PSM matching procedure. Average rating (numerical transformation details are shown in Table 4-4) of Moody's, the control agency and their differences are calculated to show the relative rating criterion gap between Moody's and the other agency. D-i-D is calculated by differencing the gap of Moody's and control agency's ratings between the treatment group firms and the control group. T-statistics of the D-i-D estimators are calculated and shown in the brackets. *** 1% significance level; ** 5% significance level; * 10% significance level

Control Agency: S&P	**Treatment Group (Firms receiving unsolicited ratings from Moody's but receiving solicited ratings from S&P)**	**Control Group (Firms receiving solicited ratings from both Moody's and S&P)**			
	(No. of Obs:934)	Matching Scheme 1: (No. of Obs: 1580) Number of nearest neighbors in the PSM matching: 2	Matching Scheme 2: (No. of Obs:2166) Number of nearest neighbors in the PSM matching: 3	Matching Scheme 3: (No. of Obs:2673) Number of nearest neighbors in the PSM matching: 4	Matching Scheme 4: (No. of Obs:5372) Number of nearest neighbors in the PSM matching: All
Average Ratings by Moody's	7.4606	7.8651	8.0078	8.1269	7.7980
Average Ratings by S&P	7.2859	8.4535	8.5090	8.5872	8.2351
Dif of Average Ratings (Moody's – S&P)	**+0.1745**	**-0.5883**	**-0.5012**	**-0.4603**	**-0.4371**
DID (Between Dif of Treatment Group and Control Group)	N.A	**+0.763*** (3.89)**	**+0.676*** (3.54)**	**+0.635*** (3.45)**	**+0.612*** (3.71)**
Control Agency: Fitch	**Treatment Group (Firms receiving unsolicited ratings from Moody's but receiving solicited ratings from Fitch)**	**Control Group (Firms receiving solicited ratings from both Moody's and Fitch)**			
	(No. of Obs: 1269)	Matching Scheme 1: (No. of Obs: 1790) Number of nearest neighbors in the PSM matching:	Matching Scheme 2: (No. of Obs:2102) Number of nearest neighbors in the PSM matching:	Matching Scheme 3: (No. of Obs:2528) Number of nearest neighbors in the PSM matching:	Matching Scheme 4: (No. of Obs:4764) Number of nearest neighbors in the PSM matching:
Average Ratings by Moody's	8.8944	8.4830	8.3698	8.4040	8.1383
Average Ratings by Fitch	8.0221	8.6674	8.5535	8.5825	8.3482
Dif of Average Ratings (Moody's – Fitch)	**+0.8723**	**-0.1845**	**-0.1837**	**-0.1785**	**-0.2099**
DID (Between Dif of Treatment Group and Control Group)	N.A	**+1.057*** (4.81)**	**+1.056*** (5.80)**	**+1.051*** (5.95)**	**+1.082*** (6.63)**

4.5.2 Rating quality of unsolicited and solicited ratings issued by Moody’s

Hypothesis 4-2 states that the qualities of unsolicited and solicited ratings are not different. The quality of Moody’s ratings is measured in two perspectives: rating predictability and timeliness.

Rating predictability of unsolicited and solicited ratings is measured by the panel regression of Distance to Default indicator on unsolicited dummy along with other control variables. Also, I supplement the test by using a predicting model of DTD to test the relative rating accuracy between solicited and unsolicited ratings.

Rating timeliness is measured by multi-agency comparison of the rating change speed. Moody’s rating change announcements are compared with those by S&P or Fitch to test who leads/lags another CRA. A higher probability of leading another agency and a lower probability of lagging another agency indicate a higher rating quality.

The empirical analysis in this section (Section 4.5.2) is accompanied with the conclusion drawn in the theoretical analysis shown in Formula 4.2.11 and Formula 4.2.13. Those two in-equations show that the unsolicited and solicited ratings provide the external investors with the extra information at the same level and the quality of the information is not weaker due to the non-solicitation status of the ratings. From the perspective of empirical analysis, I measure the concept ‘information’ by introducing two concepts, default-risk predictability (Section 4.5.2.1) and relative rating-change timeliness (4.5.2.2).

4.5.2.1 Rating predictability

The rating predictability reflects the accuracy of information provided by the ratings regarding the default risk variation of the rated firms. A rating with a higher quality should forecast the future variation of the firm’s default risk with a higher degree of accuracy. I follow Campbell et al. (2008) and Chava, S. & Purnanandam (2010) to apply Distance to Default (DTD) to quantitatively measure firms' default risk. A higher value of DTD is equivalent to a lower risk of default. To test whether the rating predictability is different for unsolicited and solicited ratings, I run a panel regression model of DTD on rating levels along with the unsolicited dummy. If the rating level is significant, it means that the rating has an ability of predicting DTD. Besides that, if the unsolicited dummy is insignificant, it provides evidence to show that the solicitation status does not impact the rating predictability.

To enhance the results of panel regressions, I compare the observed DTD of treatment group firms with the predicted DTD which is derived from the model built using the rating and DTD information of control group firms to test whether the predictability has a significant gap between unsolicited and solicited ratings. Specifically, observed rating and DTD information of control group firms who receive solicited ratings are used to build a predicting model. The corresponding estimates obtained in the predicting model with control group data (solicited rating levels) are applied to predict the DTD of treatment group firms with their actual unsolicited rating levels. If the error (gap between observed DTD and predicted DTD of treatment group firms) is not significant, the hypothesis of no difference of rating predictability is enhanced.

Regression Model

I apply random-effect panel regression of DTD on the lagged terms of rating indicators along with the unsolicited dummy. The reason of using the random-effect model rather than the fixed-effect one is that the random-effect model is able to capture the impact of firms' heterogeneity (solicitation status) on the dependent variable. If using fixed-effect regressions, the effect on DTD of independent variables (ratings and solicitation status) at the entity level would be eliminated while such effect is the objective I study (the solicitation status is at an entity level).

The length of the lagging time period ranges from 1 quarter to 1 year (4 quarters). Estimates on rating indicators demonstrate the link between past rating forecasts and the future DTD variation, a reflection of rating predictability on firm default risk. Estimates on unsolicited dummy measure the bias of rating predictability due to the solicitation status.

The panel regression is conducted based on the equation:

$$DTD_{i,t+p} = \alpha + \beta_{4-3,1} LogRating_{i,t} + \beta_{4-3,2} UnSLDummy_{i,t} + \boldsymbol{X'\gamma} + U_i + \varepsilon_{i,t} \quad (4.5.3)$$

i: the sample firms (all treatment firms are included and the selection of control firms depends on the matching schemes which are described in Section 4.4.3);

$DTD_{i,t+p}$: Distance to default of firm i at time (t+p), p=1,2,3,4;

$LogRating_{i,t}$: the logarithm of numerically-transformed ratings offered by Moody's to firm i at time t;

$UnSLDummy_i$: dummy equal to 1 if the firm *i* is unsolicited rated by Moody's at time t and 0 if it is solicited rated by Moody's at time t;

$\boldsymbol{X'}$**:** the vector of control variables and the components are the same as shown in Equation (4.1).

U_i : random-effects term.

The regression result is shown in Table 4-9.

Coefficients on $LogRating_{i,t}$ are consistently negative which provide evidence of a significant Moody's rating predictability. The intuition of the negative estimates is that a firm who receives a higher rating of Moody's (equivalent to a lower value of $LogRating_{i,t}$) will have a smaller default risk in the next 1 quarter to 4 quarters (equivalent to a higher value of DTD). Such association is significant after controlling the fundamental variables and it indicates that the past Moody's ratings provide extra information regarding future DTD variation. The results are consistent with the theoretical model findings shown in Formula 4.2.13 (credit ratings are informative regarding the firm actual status).

Coefficients on $UnSLDummy_i$ are insignificant which indicates that rating predictability of unsolicited and solicited ratings is not different. The intuition is that after I control the rating factor, the solicitation factor is not associated with the future DTD variation. In other words, the unsolicited ratings (of treatment group firms) do not over-predict or under-predict the DTD relative to solicited ratings (of control group firms). This finding is consistent with the theoretical model results of Formula 4.2.11 (unsolicited and solicited ratings are not different in terms of the predictability of firm actual status).

Table 4-9 Rating predictability test (panel regression)

This table shows the panel regression result of Equation (4.5.3). The panel regression is estimated by random-effect estimation. The sample firms include all unsolicited rating recipients in the dataset and the selection of solicited rating recipients depend on four different matching schemes of different nearest neighbor numbers in the PSM procedure. The dependent variable is the Distance to Default (DTD) of the firms at each quarter. Key independent variables are the lagged terms of logarithm of numerically-transformed rating indicator (the transformation details are shown in Table 4-4) and the unsolicited dummy. The number of lagging periods range from 1 to 4 quarters. Fundamental variables are controlled (details of fundamental variable setting are shown in Table 4-2). Region, sector, quarter and year effects are controlled. Figures in the brackets are corresponding t-statistics.

*** 1% significance level; ** 5% significance level; * 10% significance level.

Dependent Var.	DTD (Distance to Default)															
No. of lag terms	1				2				3				4			
Number of nearest neighbors in the PSM matching	2	3	4	All	2	3	4	All	2	3	4	All	2	3	4	All
LogRating	-2.01***	-1.99***	-2.40***	-2.07***	-1.74***	-1.67***	-1.94***	-1.85***	-1.56***	-1.46***	-1.75***	-1.63***	-1.39***	-1.30***	-1.55***	-1.48***
	(-7.80)	(-8.04)	(-10.4)	(-11.5)	(-5.74)	(-5.71)	(-6.95)	(-8.44)	(-6.13)	(-5.94)	(-7.60)	(-9.12)	(-5.66)	(-5.49)	(-6.97)	(-8.50)
UnSLDummy	-0.15	-0.21	-0.31	-0.51	-0.28	-0.28	-0.44	-0.52	-0.11	-0.18	-0.35	-0.50	-0.27	-0.31	-0.47	-0.59
	(-0.15)	(-0.25)	(-0.35)	(-0.58)	(-0.30)	(-0.34)	(-0.51)	(-0.62)	(-0.11)	(-0.21)	(-0.38)	(-0.54)	(-0.27)	(-0.35)	(-0.51)	(-0.62)
Fundamental Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	79	93	106	174	79	93	106	174	78	91	104	174	75	88	101	169
T	63	63	63	63	62	62	62	62	61	61	61	61	60	60	60	60
R^2	30.9%	31.4%	30.7%	29.3%	18.6%	19.2%	17.9%	16.3%	28.3%	29.2%	28.5%	26.9%	28.5%	29.7%	28.9%	26.8%

Robustness check: the mutual impact between DTD and ratings

Equation (4.5.3) only considers the unidirectional impact of current ratings on future DTD. However, it is reasonable to question whether there is a mutual impact between them. Although DTD is not directly observable in the public database, it can be calculated using components (stock prices, debt amount and risk-free interest rates) which can be collected from open sources. Therefore, past DTD may be considered by Moody's to issue current ratings. From the results of Equation (4.5.3) I have found an association between past ratings and current DTD. My robustness check tests whether the past DTD is a factor which determines the current rating level. Furthermore, I examine whether solicitation status still impacts the rating level (shown in Equation (5.1)) after I add past DTD as the explanatory variable.

The model equation is shown below and solved by the logit regression estimation.

$$R^*{}_{i,t} = \alpha + \beta_{4-4,1} DTD_{i,t-p} + \beta_{4-4,2} UnSLDummy_{i,t-p} + \varepsilon_{i,t} \qquad (4.5.4)$$

The dependent variable, $R^*{}_{i,t}$ represents the unobservable latent variable which defines the thresholds of various alternatives of credit rating levels $R_{i,t}$ of firm *i* at the quarter t. The details of the rating indicator transformation are described in Table 4-4. $DTD_{i,t-p}$ is the distance to default indicator of firm *i* at the quarter (t-p), where p=1,2,3 and 4 respectively. $UnSLDummy_{i,t-p}$ indicates the solicitation status of firm *i* at quarter (t-p) (equal to 1 if the firm *i* receives unsolicited ratings at quarter t-p and equal to 0 if it receives solicited ratings at quarter t-p). The regression results are shown in Table 4-10.

The significant link between past DTD and current ratings is observed and solicitation status is a significant factor determining rating levels after controlling past DTD. This enhances both Hypothesis 4-1 and Hypothesis 4-2. Significantly positive estimates of $\beta_{4-4,2}$ prove the same conclusion as shown in Equation (4.5.1): more conservative ratings are offered to unsolicited rating recipients by Moody's. It shows additional evidence to enhance Hypothesis 4-1.

Significantly negative estimates of $\beta_{4-4,1}$ reflect that a higher past DTD (a lower default risk) is associated with a lower transformed rating indicator (a higher current rating level). It suggests that Moody's may observe the historical DTD and regard it as a factor to determine its rating levels. Combined this with the result of Equation (4.5.1), I conclude that, 1) Moody's current ratings contain the information of past DTD; 2) Moody's offered more conservative ratings to unsolicited rating recipients after we control the factor of past DTD; 3) there is no significant gap of future DTD gap between two types of rating recipients controlling the same rating levels. In summary, although ratings are more conservative for unsolicited rating recipients, such conservatism is not biased because it accurately predicts the future DTD. It fits the hypothesis of self-selection: firms with potential bad future performances do not select to be rated, Moody's observes that and offers more conservative ratings to them to provide extra information to the market.

Table 4-10 Logit regression of ratings on past DTD and unsolicited dummy

This table shows the result of ordered logistic regression shown in Equation (4.5.4). Four matching schemes are applied to select the control group firms with different number of nearest neighbors. The dependent variable is the unobservable variable defining the thresholds of numerically transformed rating-notch indicators (details of the transformation are shown in Table 4-4). The key independent variables are DTD (t-p) and the unsolicited dummy. DTD (t-p) is the Distance to Default indicator in the quarter t-p where p ranges from 1 to 4. The unsolicited dummy is equal to 1 if the firm receives unsolicited ratings from Moody's and equal to 0 if it receives solicited ratings from Moody's. Year, quarter, country and sector are controlled. The estimation is by MLE method. Figures in the brackets are corresponding Wald-statistics.

*** 1% significance level; ** 5% significance level; * 10% significance level.

Dependent Var.	Ratings															
No. of lag terms (p)	1				2				3				4			
Matching Scheme	1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All
Unsolicited Dummy	**0.195*** (11.18)**	**0.225*** (16.39)**	**0.240*** (19.62)**	**0.122** (5.92)**	**0.175*** (8.88)**	**0.209*** (13.80)**	**0.224*** (16.76)**	**0.103** (4.68)**	**0.159*** (7.16)**	**0.193*** (11.52)**	**0.208*** (14.23)**	**0.097** (3.61)**	**0.148** (6.08)**	**0.179*** (9.71)**	**0.194*** (12.09)**	**0.081* (2.97)**
DTD（t-p）	-0.031*** (23.14)	-0.036*** (39.51)	-0.028*** (30.95)	-0.012*** (11.86)	-0.032*** (29.43)	-0.038*** (42.79)	-0.030*** (33.23)	-0.013*** (13.17)	-0.031*** (27.20)	-0.038*** (41.69)	-0.030*** (32.38)	-0.012*** (12.43)	-0.032*** (26.54)	-0.039*** (43.04)	-0.031*** (33.65)	-0.013*** (13.25)
Region Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3904	4562	5174	8812	3828	4472	5070	8639	3749	4380	4964	8465	3671	4290	4861	8293
AIC	19588.5	22871.2	25782.3	44663.7	19262.2	22469.4	25319.9	43873.0	18897.3	22041.4	24829.8	43055.2	18545.2	21637.0	24372.8	42253.5
SIC	19845.5	23134.6	26050.9	44954.2	19524.7	22738.4	25594.2	44176.8	19158.9	22309.6	25103.2	43351.1	18805.9	21904.3	24651.8	42548.4
-2Log	19506.5	22789.2	25700.3	44581.7	19178.2	22385.4	25235.9	43787.0	18813.3	21957.4	24745.8	42971.2	18461.2	21553.0	24286.8	42169.5

Predicting model method

The panel regression model analyses the treatment group firms and the control group firms in an equation and splits the two types of firms by adding a dummy variable on the right side of the regression equation. To find a more intuitive way to distinguish the unsolicited ratings from solicited ones, I use a simple regression model of DTD with only control group firm data to obtain the estimates on rating factors and then apply those estimates to the treatment group ratings to predict the DTD of unsolicited rating recipients. The predicted value is compared with the observed value to demonstrate whether the estimates create biased predicted DTD.

I use the actual observations of control group firms to estimate Equation (4.5.5). The selection of control group firms are varied according to the matching schemes (the number of nearest neighbors in the PSM procedure),

$$\mathrm{Control\_Group\_DTD}_{\mathrm{i,t+p}} = \alpha + \beta_{4-5,1}\mathrm{Control\_Group\_LogRating}_{\mathrm{i,t}} + \mathrm{X}_{\mathrm{controlGroup}}{}'\gamma + \varepsilon_{\mathrm{i,t}} \quad (4.5.5)$$

$Control\_Group\_DTD_{i,t+p}$: Distance to default of the control group firm *i* at time (*t*+*p*), *p*=1,2,3,4;

$Control\_Group\_LogRating_{i,t}$: the logarithm of numerically-transformed ratings offered by Moody's to the control group firm *i* at time *t*;

$\boldsymbol{X'}$**:** the vector of control variables and the components are the same as shown in Equation (4.5.1).

The corresponding estimates, $\hat{\alpha}, \hat{\beta}_{5,1}$ and $\hat{\boldsymbol{\gamma}}$ are obtained by the solution of Equation (4.5.5) before those estimates are applied to predict the treatment group firms' DTD ($\widehat{DTD}$) in the format of Equation (4.5.6).

$$Treatment\_Group\_\widehat{DTD}_{i,t+p} = \hat{\alpha} + \hat{\beta}_{4-5,1}Treatment\_Group\_LogRating_{i,t} + \boldsymbol{X_{treatmentGroup}}'\hat{\boldsymbol{\gamma}} \quad (4.5.6)$$

In Equation (4.5.6), $Treatment\_Group\_LogRating_{i,t}$ and $\boldsymbol{X_{treatmentGroup}}'$ are observations in the treatment group dataset. $\hat{\alpha}$, $\hat{\beta}_{4-5,1}$ and $\hat{\boldsymbol{\gamma}}$ are obtained by solving Equation (4.5.5).

The final step is to take the difference between observed $Treatment\_Group\_DTD_{i,t+p}$ and predicted $Treatment\_Group\_\widehat{DTD}_{i,t+p}$ to calculate the relative rating bias between unsolicited and solicited ratings of Moody's.

$\text{Relative Prediction Bias} = \text{Treatment\_Group\_DTD}_{\text{i,t+p}}$ - $\text{Treatment\_Group\_}\widehat{\text{DTD}}_{\text{i,t+p}}$.

A significant positive bias indicates that the actual DTD of unsolicited rating recipients is larger than the predicted DTD using estimated coefficients derived from solicited rating recipients along with actual rating of unsolicited rating recipients. Thus, the unsolicited ratings under-estimate the DTD relative to solicited ones (equivalent to over-estimate the default risk). Conversely, a significant negative bias indicates that unsolicited ratings over-estimate the DTD relative to solicited ones and an insignificant bias indicates that unsolicited ratings neither under-estimate nor over-estimate the DTD relative to solicited ones.

The results of the calculation of the average 'relative rating bias' are shown in Table 4-11.

In most of the cases shown in Table 4-11, the relative prediction bias of DTD between unsolicited and solicited ratings is insignificant which enhances my previous conclusion that the DTD predictability is not different for the two types of ratings by Moody's. In some of the cases, the bias is significantly positive showing a weak evidence that Moody's may over-estimate the future risk of default of firms (under-estimate the DTD). This finding also fits the self-selection hypothesis by showing that Moody's selects those firms whom it believes would have a worse future performance and offer unsolicited ratings to them at a more conservative level. The conservative ratings under-estimate the future DTD of the rating recipients compared with the solicited rating recipients.

Table 4-11 Rating predictability test (relative DTD prediction bias)

This table shows the result of the calculation of relative prediction bias of DTD between solicited and unsolicited ratings. The value is calculated by the equation $Treatment\_Group\_DTD_{i,t+p}$ - $Treatment\_Group\_\widehat{DTD}_{i,t+p}$. $Treatment\_Group\_DTD_{i,t+p}$ is the actual observation of DTD of unsolicited rating recipients *i* (treatment group firms) at a future point t+p (p=1 to 4 quarters) and $Treatment\_Group\_\widehat{DTD}_{i,t+p}$ is calculated in the format of Equation (5.5) using the actual observation of rating at time t along with other fundamental variables at time t, along with the estimates of prediction coefficients derived from Equation (5.4). Figures in the brackets are corresponding t-statistics,
*** 1% significance level;
** 5% significance level;
* 10% significance level.

No of Lag Terms (p)	Number of nearest neighbors in the PSM matching	No. of Obs in Solicited Rating Dataset	No. of Obs in Unsolicited Rating Dataset	Relative prediction bias of DTD
1	2	1677	1191	0.46* (1.66)
	3	2090	1191	0.12* (1.83)
	4	2591	1191	-0.03 (-0.24)
	All	5139	1191	-0.56 (-1.32)
2	2	1638	1167	0.03 (0.13)
	3	2041	1167	0.13** (2.10)
	4	2532	1167	-2.30 (-1.18)
	All	5033	1157	0.27 (0.58)
3	2	1618	1154	-1.01 (-0.75)
	3	2008	1154	0.05 (0.63)
	4	2491	1154	0.15* (1.64)
	All	4955	1154	-0.02 (-0.14)
4	2	1595	1136	0.39** (2.48)
	3	1973	1136	0.14 (1.22)
	4	2448	1136	-0.18 (-0.81)
	All	4872	1136	0.02 (0.33)

4.5.2.2 Rating timeliness

The timeliness of rating action announcements (downgrades, upgrades, warnings of rating change and the revision following the warnings) is an alternative indicator of rating quality applied in this paper. A rating agency is thought to be of higher quality if the rating changes announced by that agency are more likely to lead and less likely to lag other agencies. The timeliness reflects the information contents delivered to the market by rating action announcements. Assume I have two agencies, A and B. If announcements by A are released a couple of days before B, the information content of B's announcement should be lower than A's because the market participants have received and responded to the signal of A's announcements and would not obtain new information from B's announcements. In this paper, Moody's rating timeliness is measured by a relative lead-lag relationship of rating action announcements between Moody's and S&P (or Fitch). A higher probability of the case that 'Moody's lead S&P/Fitch', or a lower probability of the case that 'Moody's lag S&P/Fitch' indicates a better rating quality of Moody's, and vice versa. If the probability that Moody's unsolicited ratings lag or lead its peers' (S&P and Fitch) ratings is not significantly associated with Moody's solicited ratings, I find evidence to show that relative rating quality of Moody's ratings is not related to the status of solicitation.

I find that Moody's unsolicited rating changes are neither significantly faster nor significantly slower, than the solicited rating changes. It demonstrates that the rating quality of unsolicited and solicited ratings by Moody's does not have a significant difference between the two types of ratings in terms of rating timeliness.

Measurement of rating timeliness: lead-lag relationship between Moody's and the control agency

Rating timeliness is reflected by the sequence of occurrence of Moody's and other two agencies' rating actions. Rating actions of Moody's should be defined first. In the analysis of this paper, I identify three segments of rating actions: negative actions include downgrades and possible downgrade announcements; positive actions include upgrades and possible upgrade announcements and revision actions are announcements that Moody's exclude the firm from the possible downgrade/upgrade list. From the sample dataset, I identify 1191 Moody's adjustment actions for 142 sample firms in the sample period (2001Q1-2017Q4). Of them, 927 actions are taken for solicited ratings and 264 actions are for unsolicited ratings.

After identifying Moody's rating actions, I search the actions of S&P and Fitch, for each of Moody's actions, to find the cases of 'Moody's lead S&P/Fitch' and 'Moody's lag S&P/Fitch.

For each of the rating actions taken by Moody's, I find the specific actions by S&P and Fitch which satisfy the conditions as follows and identify them as the case 'Moody's *lead* S&P or Fitch': 1) they are of the same type of actions by Moody's (negative, positive or revising); 2) they occurred no more than 90 days *after* the actions of Moody's were taken. Similarly, for each of the rating actions taken by Moody's, I find the specific actions by S&P and Fitch which satisfy the conditions as follows and identify them as the case 'Moody's *lag* S&P or Fitch': 1) they are of the same type of actions by Moody's (negative, positive or revising); 2) they occurred no more than 90 days *before* the actions of Moody's were taken.

To be more intuitive, I raise two actual examples (selected from the dataset) to show how the 'Moody's lead S&P/Fitch' and 'Moody's lag S&P/Fitch' cases are identified. The examples are displayed in Appendix 4-3.

Previous literature ignores some complicated cases of lead-lag relationships where multiple rating actions of different agencies, or by same agency are taken sequentially at close dates. In these cases, Moody's actions may be identified as simultaneously 'leading' and 'lagging' S&P or Fitch, which is unreasonable from an intuition perspective. Therefore, some complicated cases are stated also in Appendix 4-3.

Comparison of lead-lag relationships between Moody's and S&P/Fitch for solicited and unsolicited cases

I analyze the lead-lag relationship for Moody-S&P and Moody-Fitch pairs respectively. For the Moody-S&P pair, 799 out of 1191 Moody's rating actions are valid to be compared with S&P actions[16]. Among all the valid actions, 117 actions (14.64% of 799) are identified as 'leading S&P and 154 actions (19.27% of 799) are identified as 'lagging S&P.

For Moody-Fitch pair, 947 out of 1191 Moody's rating actions are valid to be compared with Fitch actions[17]. Among all the valid actions, 123 actions (12.99% of 947) are identified as 'leading Fitch' and 112 actions (11.83% of 799) are identified as 'lagging Fitch'.

The details are shown in Table 4-12. Since the total number of 'revising actions' are very small, I only keep negative and positive actions in the further analysis.

Table 4-12 The detail of the lead-lag relationship between Moody's and S&P (or Fitch)

Pair	Type of actions	Total		Negative		Positive	
		Un-solicited	Solicited	Un-solicited	Solicited	Un-solicited	Solicited
Moody-S&P	No. of all valid cases of Moody's actions	116	683	60	435	45	169
	Ratio of cases when **Moody's leads S&P** out of all valid cases	11.21%	15.23%	13.33%	17.93%	11.11%	8.28%
	Ratio of cases when **Moody's lags S&P** out of all valid cases	19.83%	19.18%	26.67%	23.22%	11.11%	11.24%
Moody-Fitch	No. of all valid cases of Moody's actions	219	728	116	455	87	191
	Ratio of cases when **Moody's leads Fitch** out of all valid cases	11.42%	13.46%	14.66%	16.26%	9.20%	8.38%
	Ratio of cases when **Moody's lags Fitch** out of all valid cases	11.87%	11.81%	13.79%	14.07%	11.49%	10.47%

[16] The 'invalid' actions refer to those Moody's rating actions occurring at the date when S&P does not rate the corresponding firms so they are excluded from the analysis.
[17] The 'invalid' actions refer to those Moody's rating actions occurring at the date when Fitch does not rate the corresponding firms so they are excluded from the analysis.

To measure the relative quality of Moody's ratings, I focus on the ratio of cases when Moody's lead/lag S&P/Fitch. A higher ratio of 'Moody's leading' cases or a lower ratio of 'Moody's lagging' cases indicates a better Moody's rating quality. The comparison between ratios of unsolicited and solicited ratings show me the impact of solicitation status on relative rating qualities.

From the above table I can observe some potential slight evidence of a worse quality of unsolicited ratings than solicited ones for the negative action sample, solicited Moody's ratings have a greater proportion of cases of 'Moody's leads S&P /Fitch' than unsolicited Moody's ratings (15.32%>11.21% for Moody- S&P pairs of 'all types of actions'; 13.46%>11.42% for Moody-Fitch pairs of 'all types of actions'; 17.93%>13.33% for Moody- S&P pairs of 'negative actions'; 16.26%>14.66% for Moody-Fitch pairs of 'negative actions'). It shows that Moody's lead S&P /Fitch negative rating actions with a lower probability if the ratings are unsolicited by firms, which mirrors a worse rating quality. Except that, I do not find a consistent and significant gap between the rating timeliness of unsolicited and solicited ratings by Moody's.

To statistically test the association between solicitation status and rating timeliness, I use Chi-square test to examine the significance of the relation between the dummy indicating whether Moody's lead/lag S&P /Fitch, and the dummy indicating whether Moody's ratings are solicited or unsolicited. The response variable is the lead/lag dummy and the category variable is the solicitation status. The null hypothesis of the Chi-square test is that there is no association between lead/lag dummy variable and the solicitation variable.

The tests are taken for each type of rating actions, each PSM scheme and for each pair of rating agencies. The results of the Chi-square test are shown in Table 4-13.

I do not find a case when the association is significant by observing all Chi-square values, which are not big enough to reject the null hypothesis of no association. The results show evidence that even if I have found some potential evidence of better quality of solicited ratings in terms of timeliness (shown in Table 4-12), the association is not statistically significant (Table 4-13). Therefore, I conclude that rating qualities, regarding the rating adjustment action timeliness, are not different between Moody's solicited and unsolicited ratings.

To enhance the results of Chi-square tests, I conduct logit regressions to test the association between the solicitation status of Moody's ratings and its lead-lag relationship with S&P/Fitch's ratings. Dependent variables are dummy variables indicating whether the rating change of Moody's is followed by/follows the other two agencies (=1) or not (=0), the key independent variables are dummy variables indicating whether this corresponding firms are unsolicited rated (=1) or solicited rated (=0). Year, sector and region are also controlled in the independent variables set.

The results of logit regressions are shown in Tables 4-14 and 4-15. The situations of Moody's lead and lag the other two are separately reported in the two tables. In each table, I present the cases of negative and positive rating actions respectively and consider different PSM matching schemes.

Coefficients on 'un-solicited' dummy in the two tables report similar results as the Chi-square that significant association cannot be found, even if I find that some cases with marginally significant estimates. In the table of Moody's lead S&P/Fitch, I find marginally significantly negative estimates in negative action cases for the Moody-S&P pairs. Negative estimates, in this case, indicate a worse quality of unsolicited ratings: if the Moody's ratings are unsolicited (the dummy is 1), Moody's is less likely to lead S&P regarding negative rating actions. However, the association only exists for Moody-S&P pairs for negative actions and is not persistent for other cases.

4.5.3 Summary of the empirical results

I validate the statement of Hypothesis 4-1 by providing evidence to show that Moody's issue ratings with more conservative levels to unsolicited rating recipients. The tests are composed into two parts: the single-agency test and the multi-agency test. The single-agency test focuses on the ratings of Moody's and finds that unsolicited ratings of Moody's are lower than solicited ratings controlling fundamental factors as well as other basic variables. The multi-agency test supplements the single-agency test result by introducing the ratings issued by S&P and Fitch and applying the concepts of 'relative rating gap' between Moody's and S&P/Fitch to measure the conservatism of ratings. I find that for those firms who receive Moody's unsolicited ratings and S&P/Fitch's solicited ratings, Moody's ratings (unsolicited) are lower than S&P/Fitch's (solicited) while for those firms who receive Moody's solicited ratings and S&P/Fitch's solicited ratings, Moody's ratings (solicited) are higher than S&P/Fitch's (solicited). It shows that the solicitation status of Moody's is associated with a lower rating level (a higher value of numerically-transformed rating indicator) than its solicited counterpart. This finding also supports the conclusion drawn in the theoretical model of Formula 4.2.6.

Table 4-13 Chi Square test of association between rating action timeliness and Moody's solicitation status

This table shows the result of Chi-square test which is conducted to test the association between rating action timeliness, measured by Moody's lead-lag relationship with another rating agency, and the solicitation status. Four cases of Moody's lead-lag relationship (lag S&P, lead S&P, lag Fitch and lead Fitch) are identified. For each of the cases, the association between the dummy indicating the case (equal to 1 if the action fits the condition of lead/lag and 0 else) and solicitation status dummy (equal to 1 if the rating is unsolicited and 0 if it is solicited) is calculated in the format of Chi-square statistics. The null hypothesis of the Chi-square is that there is no association between Moody's and the control agency's lead-lag relationship and Moody's solicitation status. Figures in the cells are corresponding Chi-square statistics and figures in the brackets are p-values.

Chi-Square (p-value)	Type of Actions	All				Negative				Positive			
	Matching Scheme	1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All
Moody-S&P Pair	Moody's Lag	0.0409 (0.84)	0.0426 (0.84)	0.0016 (0.97)	0.0267 (0.87)	0.0603 (0.81)	0.0534 (0.82)	0.2862 (0.53)	0.3474 (0.56)	0.0203 (0.89)	0.1327 (0.72)	0.2340 (0.63)	0.0057 (0.94)
	Moody's Lead	1.910 (0.17)	0.6830 (0.41)	0.8702 (0.35)	1.2821 (0.26)	1.1463 (0.27)	0.3899 (0.53)	0.5129 (0.47)	0.7764 (0.38)	0.2354 (0.63)	0.4407 (0.51)	1.1329 (0.29)	0.1785 (0.68)
Moody-Fitch Pair	Moody's Lag	0.3289 (0.57)	0.7395 (0.39)	0.3171 (0.57)	0.0006 (0.98)	0.2075 (0.65)	0.3112 (0.58)	0.1348 (0.71)	0.0006 (0.98)	0.1499 (0.70)	0.4119 (0.52)	0.1669 (0.68)	0.0650 (0.80)
	Moody's Lead	1.3257 (0.25)	0.4027 (0.53)	2.0476 (0.15)	0.6236 (0.43)	0.6907 (0.41)	0.2090 (0.65)	1.2046 (0.27)	0.3511 (0.55)	0.0033 (0.95)	0.0860 (0.77)	0.1394 (0.71)	0.0508 (0.82)

Table 4-14 Logit regression of ‘Moody’s lead’ indicator on solicitation status dummies

This table reports the results of logistic regressions of ‘Moody’s lead’ dummies on solicitation status dummies. The regressions are run on the basis of Moody’s rating actions. Dependent variable is the dummy equal to 1 if the corresponding rating action is identified as leading S&P or Fitch and to 0 else. The key independent variable, ‘un-solicitation dummy’ is equal to 1 if the corresponding rating action of Moody’s is provided to unsoliciting firms and to 0 if that is provided to soliciting firms. Dummies indicating the year when the actions are taken, the sector of the rated firm, and the region where the firm is registered, are also included in the independent variables. Figures in the brackets are Wald-statistics for the corresponding estimators.

Logistic Regression	Action Type	All				Negative				Positive			
	Matching Scheme	1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All
	Dependent Variable (Dummy)	*Moody's Lead S&P/Fitch*											
Pair													
Moody-S&P	Coefficients on Un-Solicitation Dummy	-0.4516 (1.36)	-0.2978 (0.54)	-0.2953 (0.70)	-0.2821 (0.76)	-0.7744 (2.24)	-0.4264 (0.71)	-0.5293 (1.27)	-0.4321 (1.07)	0.8839 (0.74)	0.7142 (0.65)	1.0398 (1.50)	0.3677 (0.33)
	Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Region Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	323	381	471	799	192	227	287	495	94	112	130	214
	AIC	274.670	307.109	391.323	681.750	184.148	202.341	259.638	467.268	72.426	87.754	93.544	142.227
	SC	350.223	385.965	474.420	775.417	249.298	270.840	332.827	551.359	118.205	142.124	150.894	209.547
	-2LogL	234.670	267.109	351.323	641.750	144.148	162.341	219.638	427.268	36.426	47.754	53.544	102.227
Moody-Fitch	Coefficients on Un-Solicitation Dummy	-0.1036 (0.20)	-0.0197 (0.005)	-0.2086 (0.59)	-0.0334 (0.02)	-0.2421 (0.42)	-0.1021 (0.08)	-0.1981 (0.34)	0.0158 (0.002)	-0.0799 (0.02)	0.1670 (0.08)	0.1914 (0.11)	-0.0396 (0.006)
	Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Region Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	521	559	643	947	307	327	385	571	161	175	191	214
	AIC	410.437	427.103	529.400	726.154	281.567	289.581	367.732	494.165	119.732	124.130	130.260	184.737
	SC	495.552	513.626	618.723	823.220	356.104	365.380	446.797	581.113	181.360	187.426	195.305	257.289
	-2LogL	370.437	387.103	489.400	686.154	241.567	249.581	327.732	454.165	79.732	84.130	90.260	144.737

Table 4-15 Logit regression of ‘Moody’s lag’ indicator on solicitation status dummies

This table reports the results of logistic regressions of ‘Moody’s lag’ dummies on solicitation status dummies. The regressions are run on the basis of Moody’s rating actions. Dependent variable is the dummy equal to 1 if the corresponding rating action is identified as lagging S&P or Fitch and to 0 else. The key independent variable, ‘un-solicitation dummy’ is equal to 1 if the corresponding rating action of Moody’s is provided to unsoliciting firms and to 0 if that is provided to soliciting firms. Dummies indicating the year when the actions are taken, the sector of the rated firm, and the region where the firm is registered, are also included in the independent variables. Figures in the brackets are Wald-statistics for the corresponding estimators.

Logistic Regression	Action Type	All				Negative				Positive			
	Matching Scheme	1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All
	Dependent Variable (Dummy)	*Moody's Lag S&P/Fitch*											
Pair													
Moody-S&P	Coefficients on Un-Solicitation Dummy	-0.076	0.0068	0.0370	0.1698	0.0425	0.0067	0.0781	0.2193	1.0804	1.3685	0.6015	0.4338
		(0.06)	(0.005)	(0.02)	(0.42)	(0.01)	(0.003)	(0.05)	(0.45)	(1.06)	(2.04)	(0.68)	(0.45)
	Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	323	381	471	799	192	227	287	495	94	112	130	214
	AIC	336.508	403.521	492.636	794.575	232.848	281.932	341.031	560.469	79.072	94.101	109.266	150.583
	SC	412.061	482.377	575.733	888.242	297.998	350.431	414.220	644.560	124.851	148.471	166.617	217.903
	-2LogL	296.508	363.521	452.636	754.575	192.848	241.932	301.031	520.469	43.072	54.101	69.266	110.583
Moody-Fitch	Coefficients on Un-Solicitation Dummy	-0.3025	-0.2778	-0.1970	-0.0712	-0.3189	-0.2488	-0.1919	-0.1040	-0.4997	-0.4312	-0.3102	-0.2152
		(1.01)	(0.94)	(0.51)	(0.07)	(0.63)	(0.42)	(0.28)	(0.09)	(0.66)	(0.49)	(0.28)	(0.14)
	Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	521	559	643	947	307	327	385	571	161	175	191	278
	AIC	413.259	450.947	513.618	684.106	273.387	290.556	335.920	465.445	126.310	133.797	141.632	162.333
	SC	498.374	537.470	602.941	781.171	347.923	366.355	414.985	552.393	187.938	197.093	206.677	234.885
	-2LogL	373.259	410.947	473.618	644.106	233.387	250.556	295.920	425.445	86.310	93.797	101.632	122.333

Hypothesis 4-2 is related to the concept of rating quality. I use two indicators to measure the rating quality: rating predictability and rating action timeliness. For the rating predictability measure, I use Distance to Default and its relations with past ratings to test the predictability of Moody's ratings. Both the regression model method and predicting model method show the conclusion that there is no gap between the predictability of unsolicited and solicited ratings. For the rating action timeliness, I identify Moody's rating actions and match each of these with the actions taken by S&P and Fitch to define the cases of 'Moody's lead S&P/Fitch' or 'Moody's lag S&P/Fitch'. I find that the likelihood of either of the two cases is not associated with the solicitation status, which demonstrates that rating timeliness is not a function of solicitation status. The empirical results for Hypothesis 4-2 also fit the theoretical discussion in Formula 4.2.11 and Formula 4.2.13.

4.6 Conclusion

This paper studies the association between rating solicitation and rating levels as well as rating qualities. An empirical analysis is conducted to show evidence for the self-selection hypothesis: weak firms tend to opt not to be rated by rating agencies and rating agencies take the solicitation status into account and rate lower for those unsolicited rating recipients.

My research is designed to identify the phenomenon of more conservative ratings for unsolicited cases than for solicited cases and justify ratings' behavior of unsolicited rating conservatism by observing same rating quality for both types of ratings. By the simplified theoretical model, I conclude that if the self-selection hypothesis holds I would have two findings: 1) the solicitation status implies the rating agencies about the potential quality of the firms so it is rational for them to rate unsoliciting firms with lower rating levels and 2) the rating quality (i.e. the information provided by both types of ratings) should be at the similar level.

Those two hypothesized theoretical findings based on the self-selection assumption is empirically enhanced.

I find that controlling for the fundamentals, Moody's unsolicited ratings are significantly lower than solicited ratings. The result is supplemented by the investigation of multi-agency comparison which finds that Moody's unsolicited ratings are lower than solicited ratings for the same firms offered by S&P and Fitch.

To examine the rating quality, I use two measures, rating predictability and rating action timeliness, to reflect the rating quality and compare the average quality between solicited and unsolicited ratings. No significant gap of rating quality is found which demonstrates that unsolicited ratings are not related to a deterioration of rating quality. Both findings enhance the two sub-hypotheses of self-selection hypothesis: ratings are more conservative in solicited rating cases and unsolicited ratings are rational in terms of rating quality.

In conclusion, the findings in this paper justify Moody's behavior of offering lower ratings for unsolicited rating recipients and show that unsolicited ratings still provide useful information regarding firms' risk of default for market participants even though rating agencies neither charge fees nor collect internal information from rated firms in unsolicited rating decision. This is in accordance with the claim of Moody's and financial regulators who believe that unsolicited ratings are not biased and provide transparency to the market.

My research is restricted by data access and does not consider the stock returns as an indicator of rating quality. Further research may be conducted to include this indicator to reflect the rating quality more comprehensively.

5 Chapter V: Conclusions

Those who cannot learn from history are doomed to repeat it.

-- George Santayana

5.1 Summary of the essays

This thesis starts with an introduction of a phenomenon in the contemporary financial market: the role transformation of CRAs from a pure information provider to a mixture of an information provider and a market influencer. The initial aim of the establishment of the credit rating industry was to reduce the information gap between firms (borrowers) and investors (lenders), which refers to the role of information providers. However, with the expansion of the CRA business, the strong reliance of investors on the opinions given by the CRAs and the creation of rating-based regulation clauses linking the compulsory actions of financial market participants (forced selling, capital requirement holding etc.) with the ratings given by specific CRAs, CRAs have gradually become not only professional institutions providing information for investors, but also an essential participant influencing the financial market.

In the three independent studies following the introduction, I investigate the behavior of CRAs and the reaction of other financial market participants in the context of this role transformation. For the demand side of the credit rating industry, rated entities can be categorized in three types: sovereign countries, innovative financial products (for example, ABS) and individual firms (including banks). Therefore, the three independent studies are focused on sovereign ratings (Chapter II), ABS ratings (Chapter III) and firms (Chapter IV). Besides, for the supplying side of the credit rating industry, the key components of the CRA’s function can be categorized in three perspectives: the information transmission channel, investors’ reaction to rating changes and the rating bias due to the conflict of interests. Therefore, the three studies cover the topics of the information channel of sovereign ratings (Chapter II), the connection between market prices and rating levels/changes (Chapters II and III) and the effect of fee payment models on the rating quality (Chapter IV).

Sections 5.1.1 to 5.1.3 show the summary of the main findings of three chapters and in Section 5.2 I show the limitations of my thesis and raise some potential topics in the further research.

5.1.1 Extra information provided by bank rating downgrades which follow sovereign rating downgrades

In Chapter II, I present my first paper where I study the information transmission channel in the case of 'sovereign rating downgrades → bank rating downgrades → bank performances'. My main findings are: 1) sovereign rating downgrades and bank rating downgrades are both associated with a negative shock of stock returns for downgraded banks (short-term) and with an increase of bank insolvency risk (long-term); 2) the bank rating downgrades provide extra information to the market even if they follow sovereign ratings in a very short interval.

The first conclusion is drawn by an empirical finding that the downgrade of sovereign ratings is a significant factor of the stock return decrease in the time window of no more than 10 transaction days and of the increase of Z scores in the following year. The degree of stock return drop and Z score rise is higher if the sovereign rating downgrades are followed by bank rating downgrades in certain intervals.

I obtain the second conclusion by additionally applying 'sovereign ceiling policy' which creates an exogenous shock to the bank downgrades which compulsorily follow sovereign downgrades. I find that if the bank downgrades are triggered by the ceiling policy (which are 'semi-active' because the ratings are downgraded partially due to an external policy), the corresponding shock on both the stock returns and Z scores is weaker than those downgrades not triggered by the ceiling policy (which are 'fully-active' because the rating downgrades are not regulated by external policies).

In sum, this chapter shows evidence that the information released by sovereign ratings is enhanced by the following of bank ratings. In other words, sovereign ratings affect the bank performances partially via the channel of bank ratings. This finding contributes the strand of literature which discusses the channel by which sovereign ratings impact domestic commercial banks.

5.1.2 The ABS price reaction to credit ratings and the weakening of such connection after the global financial crisis

The second paper (Chapter III) is an empirical investigation on the ABS market and its relationship with credit ratings. I test the link between prices of ABS for different tranches and the levels/changes of credit ratings issued for the corresponding ABS tranche. The test is conducted for both the issuance period and the transaction period of ABS. For the issuance period, I find a significant relationship between the issuance spreads (the component of yields which is above the benchmark rate) and the issuance ratings given to the ABS. For the transaction period, I find that the transaction prices of ABS are sensitive to the changes of ABS ratings in no more than a 5-day interval (the reaction is more sensitive for downgrades than for upgrades).

Furthermore, I empirically check whether the link between issuance/transaction prices of ABS and levels/changes of credit ratings has been weaker since the 2008 global financial crisis. The data analysis result shows a weaker connection after the crisis by significant D-i-D estimates on the interaction terms between the rating factors and the post-crisis dummy.

The strong link between ABS spreads/prices and the ratings implies a reliance of ABS investors on the CRAs. This is consistent with the general topic of this thesis: the role transformation of CRAs from information providers to market influencers. ABS is a financial innovation which is associated with a very complex structure and payment mechanism. Therefore, investors are more likely to turn to the CRAs, who are regarded as professional institutions, to price ABS products. However, the findings of a weaker link in the post-crisis period indicate that the role of market influencers has been weakened since the big shock of the financial crisis.

5.1.3 The comparison of levels and qualities between unsolicited and solicited ratings

In Chapter IV, I study the issue of conflict of interests, which is a widely-discussed topic within the credit rating field. The conflict of interests is measured by the effect of solicitation status (i.e. whether the rating is paid by the issuers) on the rating levels and rating qualities. I find theoretical evidence to show a self-selection effect of unsolicited rating recipients: given the assumption that weak firms are less likely to solicit the rating services from big CRAs, CRAs regard the fact that a firm does not solicit rating services from them as a negative signal of the firm's actual quality and then rate them at a lower level compared with those firms who solicit the rating services. In the context of self-selection hypothesis, two facts should be observed: the ratings given to unsolicited rating recipients are lower than those given to solicited rating recipients, and the rating quality in terms of their predictability of default risks is not related to the solicitation status.

I find empirical evidence to support the two facts drawn by the theoretical model. By analyzing the data of unsolicited ratings issued by Moody's, I find that rating levels are lower for unsolicited ratings than for solicited ratings. This conclusion is consistent for the single-CRA test, which only analyzes the ratings given by Moody's, and for the multi-CRA test, which uses the ratings given by other two CRAs (S&P and Fitch) as the benchmark. In addition, the link between past ratings and future variation of default risks (measured by Distance to Default) is not affected by the solicitation status. The test of default risk predictability is further supplemented by taking rating change timeliness into account as another indicator of the rating quality. I also find that the rating timeliness is not related to the solicitation status.

The finding of self-selection effect indicates that although CRAs rate firms lower if the firms do not pay them, it does not negatively impact the quality of the unsolicited ratings.

5.2 Limitations and future research

Restricted by the data availability, the time constraint and research capabilities, my thesis has some limitations in terms of the following perspectives.

In Chapter II, I determine the channel of bank ratings in the information transmission of sovereign ratings. However, other potential channels, which have been discussed by the literature, are not included in my study. Those potential channels are the government debt held by banks, government guarantee for domestic banks and the free capital mobility factor.

Furthermore, in order to have a sufficient number of sovereign rating downgrades in the sample, I only study the PIIGS countries. Moreover, to identify the case of 'bank downgrades triggered by sovereign ceiling policy', I only include downgrade cases, but not upgrade cases in my analysis.

In Chapter III, as the financial market experienced a huge change after the financial crisis, it may be questionable whether the ratings can be directly compared for the pre- and post-crisis periods. For example, due to the restricted data availability, I only obtain the data of ABS market liquidity in the post-crisis period and hence am unable to show whether the liquidity in the secondary ABS market is significantly smaller after the crisis, which creates the result of a weaker ABS price reaction to rating changes. In addition, the reason why ABS prices follow credit ratings at a lower degree after the crisis is not discussed in details. Although I raise some possible explanations, such as the reputational collapse of CRAs and the issuance of the Dodd-Frank Act which aims at reducing the power of CRAs, these reasons are not empirically tested in my research.

Regarding Chapter IV, compared with solicited ratings, Moody’s published only a very few unsolicited ratings. That causes a problem of imbalanced data. I use the propensity score matching (PSM) method to match each of the unsolicited ratings by their counterparties in the solicited rating sample. However, the issue of imbalanced data cannot be fully solved by PSM. Furthermore, stock return reactions are not used to reflect the rating quality due to the limited data availability of unsolicited rating recipients with stock price records.

To address these limitations, I raise some potential topics for my future research. Firstly, the channels by which sovereign ratings affect the bank performances should be comprehensively studied. Additionally, it is worth investigating the reasons why the reactions of ABS investors after the financial crisis have become weaker and studying whether this is a consequence of the issuance of the Dodd-Frank Act. Lastly, data of other CRAs who issue more unsolicited ratings as well as the stock market information of unsolicited rating recipients could be used to research the effect of solicitation status on the rating quality.

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Appendices

Appendix 2-1

Descriptive statistics of Model 2-1-1

Table.A 1

Variable	N	Mean	Std Dev
Stock Return [t-1,t+1]	187500	-0.000121988	0.0348363
Stock Return [t-1,t+2]	187475	-0.000166806	0.0431962
Stock Return [t-1,t+3]	187450	-0.000200847	0.0505099
Stock Return [t-1,t+4]	187425	-0.000248617	0.0566510
Stock Return [t-1,t+5]	187400	-0.000289436	0.0623842
Stock Return [t-1,t+6]	187375	-0.000328920	0.0676327
Stock Return [t-1,t+7]	187350	-0.000382462	0.0722174
Stock Return [t-1,t+8]	187325	-0.000447901	0.0762606
Stock Return [t-1,t+9]	187300	-0.000513571	0.0800666
Stock Return [t-1,t+10]	187275	-0.000573620	0.0838586
Stock Return [t-1,t+20]	187050	-0.0010692	0.1116042
Stock Return [t-2,t+1]	187500	-0.000082719	0.0237996
Average_Rating (Numerically-transformed)	176722	19.9975008	11.6755509

Appendix 2-2

Table.A 2

Time window	(0,1)	(0,2)	(0,3)	(0,4)	(0,5)	(0,6)	(0,7)	(0,8)	(0,9)	(0,10)
SRD[a]	-4.33***	-4.51***	-4.36***	-4.16***	-4.28***	-4.96***	-5.07***	-5.21***	-5.47***	-4.63***
	(-15.56)	(-14.48)	(-11.31)	(-9.24)	(-8.47)	(-8.90)	(-8.40)	(-8.08)	(-8.06)	(-6.52)
Index Return	1.01***	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.10***
	(284.14)	(289.47)	(291.49)	(290.67)	(289.72)	(288.86)	(288.38)	(288.57)	(290.25)	(291.65)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Rating Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RL*SRD Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	30.37%	31.15%	31.51%	31.45%	31.39%	31.35%	31.37%	31.48%	31.83%	32.17%
N	25	25	25	25	25	25	25	25	25	25
T	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491

Table.A 3

Time window	(0,1)	(0,2)	(0,3)	(0,4)	(0,5)	(0,6)	(0,7)	(0,8)	(0,9)	(0,10)
SDR_Followed by BR[a]	-5.01***	-5.31***	-5.60***	-5.40***	-5.47***	-4.88***	-5.17***	-5.09***	-5.45***	-5.38***
	(-21.05)	(-15.49)	(-13.20)	(-10.88)	(-9.82)	(-7.96)	(-7.77)	(-7.17)	(-7.30)	(-6.74)
Index Return	1.01***	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.09***
	(284.20)	(289.56)	(291.57)	(290.75)	(289.78)	(288.88)	(288.38)	(288.57)	(290.26)	(272.24)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level (RL) Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RL*SR Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	30.39%	31.17%	31.53%	31.46%	31.40%	31.34%	31.35%	31.47%	31.82%	29.28%
N	25	25	25	25	25	25	25	25	25	25
T	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491

Table.A 4

Time window	(0,1)	(0,2)	(0,3)	(0,4)	(0,5)	(0,6)	(0,7)	(0,8)	(0,9)	(0,10)
SDR_Followed by BR	-0.058***	-0.060***	-0.056***	-0.054***	-0.055***	-0.057***	-0.061***	-0.062***	-0.060***	-0.062***
	(-32.26)	(-23.10)	(-17.53)	(-14.51)	(-13.23)	(-12.44)	(-12.16)	(-11.53)	(-10.67)	(-10.29)
At the Ceiling	0.024***	0.049***	0.074***	0.077***	0.078***	0.027***	-0.012	-0.010	-0.010	-0.044
	(5.36)	(7.64)	(9.33)	(8.25)	(7.44)	(2.29)	(-0.96)	(-0.73)	(-0.67)	(-2.90)
SDR_Followed by BR	0.041***	0.020***	0.009	-0.016	-0.014	0.041***	0.080***	0.076***	0.061***	0.011***
∗ At the Ceiling	(7.98)	(2.71)	(0.96)	(-1.45)	(-1.16)	(3.05)	(5.56)	(4.94)	(4.41)	(6.29)
Index Return	1.01***	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.11***
	(284.86)	(289.89)	(291.73)	(290.90)	(289.94)	(289.03)	(288.54)	(288.71)	(290.37)	(6.29)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level (RL) Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RL*Followed Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	30.72%	31.34%	31.63%	31.54%	31.47%	31.40%	31.40%	31.52%	31.86%	29.32%
N	25	25	25	25	25	25	25	25	25	25
T	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491

Appendix 2-3

Table.A 5

Time window	(-1,1)	(-1,2)	(-1,3)	(-1,4)	(-1,5)	(-1,6)	(-1,7)	(-1,8)	(-1,9)	(-1,10)	(-1,20)
SRD[a]	-4.08***	-4.22***	-4.06***	-3.87***	-3.99***	-4.72***	-4.84***	-4.97***	-5.22***	-4.37***	-0.69
	(-13.11)	(-10.95)	(-9.01)	(-7.66)	(-7.16)	(-7.81)	(-7.51)	(-7.32)	(-7.35)	(-5.89)	(-0.99)
Index Return	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.10***	1.10***	1.12***
	(289.25)	(291.40)	(290.62)	(289.70)	(288.79)	(288.36)	(288.59)	(290.30)	(292.02)	(293.15)	(303.04)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Rating Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RL*SRD Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	31.14%	31.51%	31.47%	31.40%	31.35%	31.35%	31.47%	31.82%	32.17%	32.43%	34.76%
N	25	25	25	25	25	25	25	25	25	25	25
T	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491	7482

Table.A 6

Time window	(-1,1)	(-1,2)	(-1,3)	(-1,4)	(-1,5)	(-1,6)	(-1,7)	(-1,8)	(-1,9)	(-1,10)	(-1,20)
SDR_Followed by BR[a]	-5.38***	-5.70***	-6.01***	-5.83***	-5.87***	-5.23***	-5.43***	-5.36***	-5.71***	-5.16***	-2.16**
	(-15.69)	(-13.43)	(-12.11)	(-10.43)	(-9.57)	(-7.86)	(-7.66)	(-7.17)	(-7.30)	(-6.31)	(-2.02)
Index Return	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.10***	1.10***	1.12***
	(289.32)	(291.49)	(290.70)	(289.78)	(288.79)	(288.38)	(288.61)	(290.31)	(292.04)	(293.17)	(303.05)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level (RL) Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RL*SR Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	31.17%	31.53%	31.49%	31.42%	31.35%	31.36%	31.47%	31.82%	32.17%	32.43%	34.76%
N	25	25	25	25	25	25	25	25	25	25	25
T	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491	7482

Table.A 7

Time window	(-1,1)	(-1,2)	(-1,3)	(-1,4)	(-1,5)	(-1,6)	(-1,7)	(-1,8)	(-1,9)	(-1,10)	(-1,20)
SDR_Followed by BR	-0.064***	-0.066***	-0.062***	-0.061***	-0.062***	-0.064***	-0.067***	-0.068***	-0.066***	-0.065***	-0.006
	(-25.04)	(-20.73)	(-16.72)	(-14.52)	(-13.46)	(-12.83)	(-12.63)	(-12.10)	(-11.27)	(-10.56)	(-0.85)
At the Ceiling	0.042***	0.070***	0.098***	0.100***	0.101***	0.043***	-0.0004	0.005	0.004	-0.032**	-0.041*
	(6.46)	(8.73)	(10.46)	(9.56)	(8.75)	(3.42)	(-0.03)	(0.25)	(0.27)	(-2.06)	(-2.04)
SDR_Followed by BR	0.039***	0.015*	0.017	-0.023*	-0.022	0.039***	0.038***	0.078***	0.063***	0.012***	0.040*
* At the Ceiling	(5.21)	(1.65)	(1.57)	(-1.94)	(-1.64)	(2.73)	(5.44)	(4.80)	(4.32)	(6.32)	(1.83)
Index Return	1.04***	1.05***	1.06***	1.07***	1.08***	1.08***	1.09***	1.09***	1.10***	1.10***	1.12***
	(292.55)	(291.82)	(290.90)	(289.98)	(289.05)	(288.56)	(288.79)	(290.47)	(292.16)	(293.29)	(303.05)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level (RL) Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RL*Followed Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	31.67%	31.69%	31.60%	31.50%	31.44%	31.42%	31.53%	31.87%	32.22%	32.48%	34.76%
N	25	25	25	25	25	25	25	25	25	25	25
T	7500	7499	7498	7497	7496	7495	7494	7493	7492	7491	7482

Appendix 2-4

Table.A 8

Model	2.2.1		
Rating Agency	Moody	S&P	Fitch
SRD	-3.90	-4.28*	-2.62
	(-1.36)	(-1.79)	(-0.94)
Firm Size	-0.15**	-0.14**	-0.15**
	(-2.33)	(-2.23)	(-2.26)
RoA	1.47**	1.47***	1.57**
	(2.30)	(2.35)	(2.42)
NPL Ratio	-16.9**	-16.5**	-16.2*
	(-2.10)	(-2.05)	(-1.91)
Deposit Ratio	0.09	0.09	0.11
	(0.73)	(0.73)	(0.81)
Firm Fixed Effect	Yes	Yes	Yes
R2	19.51%	19.75%	18.51%
N	29	29	26
T	23	23	23

Table.A 9

Model	2.2.2			2.2.3		
Rating Agency	Moody	S&P	Fitch	Moody	S&P	Fitch
SRD_Followed by BR	-5.97*	-6.72**	-9.30**	-7.79**	-9.09***	-15.24
	(-1.92)	(-2.18)	(-2.35)	(-2.46)	(-2.69)	(-1.12)
At the Ceiling	--	--	--	4.40	3.84	6.49*
				(1.31)	(0.78)	(1.71)
SRD_Followed by BR * At the Ceiling	--	--	--	2.14	1.41*	16.34**
				(0.34)	(1.63)	(2.39)
Accounting-Based Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R2	18.61%	19.46%	19.13%	19.17%	19.72%	80.50%
N	29	29	26	29	29	26
T	23	23	23	23	23	23

Appendix 3-1

Table.A 10

		Non-MBS Dataset						MBS Dataset					
		Mean	Std	Q1	Median	Q3	Range	Mean	Std	Q1	Median	Q3	Range
Pre-Crisis	Ln(Spread)	4.15	1.25	3.37	4.03	5.08	8.52	3.88	1.04	3.14	3.83	4.61	8.23
	Par_amount($\times 10^8$)	1.43	2.90	0.19	0.41	1.44	87	2.01	3.81	0.18	0.44	1.97	57.00
	CPN (%)	2.16	2.21	0.63	1.13	3.22	25.25	2.61	12.07	0.69	1.42	3.94	932.78
	Tranche_num	3.61	2.38	2	3	5	21	6.03	6.46	2	4	8	67
	Length (year)	22.34	14.53	11.97	15.48	35.31	92.84	28.83	13.65	14.8	31.3	37.7	93.10
	WAL (year)	7.04	2.86	5	7	9	19.76	4.75	2.75	2.7	4.8	6.0	40.77
	WAC (%)	7.62	3.41	5.1	7.1	9.1	22.49	5.82	1.78	4.40	5.68	7.02	13.11
	Issuer size (%)	0.27	0.90	0.013	0.03	0.09	4.68	0.15	0.21	0.021	0.075	0.16	1.05
	Credit_support (%)	17.17	17.50	5.00	12.40	24.56	148.76	13.08	16.46	2.75	8.56	18.02	194.60
	Number of CRAs rating the security (N)	2.24	0.51	2	2	3	3	2.55	0.59	2	3	3	3
	Number-format Average rating (NR)	3.72	2.97	1	3	6	16	4.24	3.48	1	3.33	6.5	20.5
During-Crisis	Ln(Spread)	4.91	0.98	4.24	4.83	5.62	6.17	4.83	0.85	4.25	4.87	5.52	4.71
	Par_amount($\times 10^8$)	2.98	6.24	0.23	0.66	3.07	99.12	2.58	5.41	0.16	0.47	2.50	60.00
	CPN (%)	2.56	2.48	1.04	1.74	3.24	25.60	2.83	2.12	1.31	2.22	3.85	10.93
	Tranche_num	3.25	2.38	1	3	4	21	4.11	3.36	2	3	5	22
	Length (year)	15.99	11.98	7.18	12.01	21.17	57.80	35.56	13.77	30.0	32.1	42.6	83.68
	WAL (year)	4.84	3.05	2.16	4.16	7.1	16.36	5.71	4.36	3	5	7	29.70
	WAC (%)	7.50	2.79	5.48	6.15	9.92	16.85	6.54	2.47	4.91	5.42	8.51	10.50
	Issuer size (%)	0.41	1.08	0.011	0.033	0.165	4.68	0.10	0.11	0.034	0.053	0.115	0.58
	Credit_support (%)	22.15	23.39	7.29	16.84	25.69	99.20	9.40	14.84	3.39	7.53	16.60	118.66
	Number of CRAs rating the security (N)	2.16	0.66	2	2	3	3	2.03	0.68	2	2	2.5	2
	Number-format Average rating (NR)	3.55	3.37	1	1.5	6	21	4.00	4.05	1	2.5	6	20
Post-Crisis	Ln(Spread)	5.31	0.82	4.91	5.38	5.93	4.63	5.05	0.73	4.70	5.04	5.52	6.88
	Par_amount($\times 10^8$)	1.69	3.60	0.20	0.36	2.07	60.4	3.21	5.20	0.38	1.22	4.00	60.00
	CPN (%)	2.92	1.83	1.60	2.54	4.07	16.56	2.83	2.28	1.35	2.17	3.64	16.72
	Tranche_num	3.89	2.92	2	3	5	22	4.06	3.50	2	3	5	21
	Length (year)	12.94	9.04	10.03	11.90	12.10	88.56	31.34	14.13	17.1	31.2	40.8	81.68
	WAL (year)	5.56	3.02	2.95	5.50	7.74	29.80	4.50	2.66	2.70	4.80	5.10	19.45
	WAC (%)	6.60	3.27	4.43	5.47	8.05	10.69	4.47	1.49	3.83	4.55	4.80	12.38
	Issuer size (%)	0.22	0.77	0.018	0.043	0.108	4.68	0.19	0.19	0.037	0.14	0.28	0.76
	Credit_support (%)	19.80	14.84	7.91	16.90	27.38	108.65	18.92	22.56	2.50	8.69	30.00	105.70

	Non-MBS Dataset						MBS Dataset					
	Mean	Std	Q1	Median	Q3	Range	Mean	Std	Q1	Median	Q3	Range
Number of CRAs rating the security (N)	1.99	0.39	2	2	2	3	1.93	0.69	1	2	2	2
Number-format Average rating (NR)	2.73	2.51	1	1.5	4.5	20	3.10	3.65	1	1	5	21

Appendix 3-2

Table.A 11

	Moody's		S&P		Fitch	
	Non-MBS	MBS	Non-MBS	MBS	Non-MBS	MBS
Par Amount (10^{-9})	-1.9***	-1.29***	-1.2***	-1.6***	-0.90**	-0.86***
	(32.3473)	(87.3684)	(6.9927)	(110.1335)	(3.7893)	(32.9519)
Coupon Rate	-0.00031	0.0474**	0.2395***	0.1897***	0.3141***	0.0174
	(0.0000)	(4.9689)	(7.7046)	(75.1078)	(9.9990)	(0.5876)
Tranche Sequence	0.4692***	0.0628***	0.3936***	0.0328***	0.3240***	0.0570***
	(75.8159)	(115.3459)	(46.7496)	(30.8032)	(35.4680)	(83.8241)
Length	-0.00998	-0.00127	0.00719	0.00465	-0.00040	-0.0232***
	(0.6296)	(0.0699)	(0.2982)	(0.8615)	(0.0005)	(17.9669)
WAL	0.1835***	0.0584***	-0.0732	0.0319*	0.0152	-0.00279
	(11.8998)	(13.1131)	(1.4904)	(3.5079)	(0.0642)	(0.0225)
WAC	0.0290	-0.0245	0.1617**	0.1039**	0.1618***	0.0995**
	(0.2479)	(0.3365)	(6.5776)	(5.4491)	(7.2307)	(4.1327)
Credit Support	-0.0122**	-0.0180***	-0.0106	-0.0391***	-0.0239***	-0.0339***
	(3.6119)	(36.2812)	(2.2433)	(118.0042)	(9.6700)	(89.2261)
Issuer size	-3.4378	-1.8281***	-9.0443***	-2.9645***	-0.5727	-0.3827
	(2.5186)	(11.8296)	(13.8429)	(27.7552)	(0.0605)	(0.4193)
Rating competition	-0.2369	-0.2896***	-3.0014***	-1.3456***	-1.8533***	-2.6129***
	(1.2431)	(17.1006)	(97.5741)	(316.6237)	(51.8702)	(778.2366)
Post-crisis dummy	**0.2582**	**-0.7523**	**7.1066**	**-1.2773**	**8.5834**	**12.0868**
	(0.0389)	**(0.8779)**	**(0.0020)**	**(2.4519)**	**(0.0028)**	**(0.0065)**
No. of Observations	439	2522	439	2522	439	2522
AIC	1564.891	2522	1100.068	9716.355	1101.559	7801.624

Appendix 3-3 Estimates on Control Variables of Model 3-1 and Model 3-2

Table A.12

	Non-MBS		MBS	
Model	3-1	3-2	3-1	3-2
Par_amount($\times 10^8$)	-0.029***	-0.036***	-0.0078	-0.0049
	(-2.63)	(-4.67)	(-1.48)	(-1.19)
CPN (%)	0.290***	0.242***	0.112***	0.095***
	(11.10)	(12.41)	(12.51)	(13.95)
Tranche_num	0.024	-0.0251*	0.0018	0.000085
	(1.34)	(-1.71)	(0.72)	(0.43)
Length (year)	0.0002	0.0031	-0.0068***	-0.0063***
	(0.05)	(0.94)	(-3.36)	(-3.99)
WAL (year)	0.024	0.044***	0.059***	0.067***
	(1.33)	(3.31)	(8.83)	(12.88)
WAC (%)	-0.03*	-0.0045	-0.081***	0.047***
	(-1.92)	(-0.35)	(-5.60)	(3.8)
Issuer Size (%)	2.450***	3.005***	0.701***	0.194
	(3.49)	(6.02)	(3.23)	(1.14)
Credit_support (%)	-0.0053***	-0.0051***	0.0009	-0.0043***
	(-2.46)	(-3.38)	(0.73)	(-4.66)
CLO_dummy	-0.715***	-0.711***	--	--
	(-4.80)	(-6.76)		
Auto_dummy	0.153	-0.274***	--	--
	(1.15)	(-2.78)		
Collateral_CMBS_dummy	--	--	-0.419***	-0.145***
			(-7.06)	(-3.07)
Collateral_RMBS_dummy	--	--	-0.697***	-0.316***
			(-6.52)	(-3.75)
Collateral_Wholesale_dummy	--	--	-0.324***	-0.487***
			(-3.84)	(-7.38)
Country_KY	0.667***	0.491***	--	--
	(3.38)	(3.52)		
Country_US	-0.130	0.052	0.780***	0.147**
	(-0.85)	(0.48)	(9.37)	(2.15)
Country_GB	0.457**	0.074	1.051***	0.326***
	(2.57)	(0.58)	(13.25)	(4.69)
Country_AU	-0.039	-0.273*	0.692***	0.058
	(-0.17)	(-1.67)	(5.20)	(0.55)
Country_NL	0.374**	0.135	1.018***	0.360***
	(2.19)	(0.12)	(16.53)	(7.1)
Country_IE	-0.75***	-0.48***	0.795***	0.512***
	(-4.29)	(-3.62)	(10.44)	(8.52)

Appendix 3-4

Table.A 13

	Non-MBS						MBS					
Column	A-Equation (3-1)			B- Equation (3-2)			C- Equation (3-1)			D- Equation (3-2)		
Number-format Average rating (NR)	0.02* (1.66)	0.05*** (6.11)	0.09*** (42.21)	0.12*** (7.30)	0.12*** (9.03)	0.13*** (52.62)	0.12*** (23.17)	0.11*** (26.05)	0.12*** (39.91)	0.16*** (28.28)	0.15*** (33.12)	0.16*** (48.75)
Number of CRAs rating the security (N)	0.05 (1.06)	0.06 (1.47)	0.01 (0.93)	0.05 (0.96)	0.05 (1.29)	0.002 (0.20)	-0.004 (-0.15)	-0.03 (-1.23)	0.003 (0.18)	0.02 (0.73)	0.02 (0.79)	0.04** (2.28)
during_crisis (DC)	--	--	--	0.98*** (4.89)	0.71*** (3.98)	1.17*** (23.54)	--	--	--	1.47*** (9.20)	1.36*** (11.77)	1.34*** (15.69)
post_crisis (PC)	--	--	--	0.91** (2.33)	0.89** (2.11)	1.32*** (5.41)	--	--	--	1.08*** (3.36)	0.92*** (3.69)	0.82*** (4.38)
NR× DC	--	--	--	-0.11*** (-3.91)	-0.08*** (-4.33)	-0.12*** (-18.33)	--	--	--	-0.15*** (-6.39)	-0.12*** (-8.68)	-0.10*** (-9.41)
NR× PC	--	--	--	-0.13*** (-7.14)	-0.12*** (-6.68)	-0.11*** (-24.86)	--	--	--	-0.14*** (-12.49)	-0.15*** (-15.72)	-0.15*** (-21.69)
Country Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Char. Control 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Char. Control 2	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Char. Control 3	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
N	248	590	9985	248	590	9985	1652	2129	4609	1652	2129	4609
Adj. R2	85.82%	68.90%	74.83%	88.60%	71.23%	77.19%	65.22%	61.78%	56.20%	69.39%	67.26%	62.03%

Appendix 3-5

Table.A 14

		Time windows					
		1 day		3 days		5 days	
	Boundary	dE	dP × dE (δ)	dE	dP × dE (δ)	dE	dP × dE (δ)
'Significant' Area	2007.9.15	-0.54***	0.51***	-0.33***	0.38***	-0.28***	0.21***
		(-6.72)	(3.54)	(-7.03)	(4.53)	(-7.52)	(3.15)
	2008.9.15	-0.48***	0.45***	-0.29***	0.38***	-0.25***	0.15**
		(-6.38)	(2.85)	(-6.71)	(4.07)	(-7.08)	(2.05)
	2008.11.15	-0.47***	0.43***	-0.26***	0.21**	-0.25***	0.17**
		(-6.29)	(2.66)	(-5.87)	(2.29)	(-7.20)	(2.27)
	2009.1.15	-0.47***	0.41**	-0.25***	0.22**	-0.25***	0.16**
		(-6.22)	(2.51)	(-5.86)	(2.26)	(-7.14)	(2.12)
	2009.3.15	-0.44***	0.35**	-0.24***	0.18*	-0.24***	0.11
		(-6.01)	(1.98)	(-5.65)	(1.72)	(-6.91)	(1.42)
'Insignificant' Area	2009.5.15	-0.42***	0.30	-0.23***	0.13	-0.24***	0.20**
		(-5.85)	(1.48)	(-5.46)	(1.14)	(-7.28)	(2.26)
	2009.7.15	-0.41***	0.28	-0.22***	0.12	-0.24***	0.19**
		(-5.82)	(1.33)	(-5.42)	(0.96)	(-7.23)	(2.06)
	2009.9.15	-0.40***	0.23	-0.22***	0.08	-0.23***	0.16
		(-5.74)	(0.95)	(-5.35)	(0.55)	(-7.09)	(1.51)
	2009.11.15	-0.39***	0.18	-0.21***	0.03	-0.22***	0.31
		(-5.67)	(0.68)	(-5.27)	(0.21)	(-6.98)	(1.11)
	Security Fixed Effect			Yes			
	Year Fixed Effect			Yes			
	Rating-level Control			Yes			
	T			3914			
	N			72			

Appendix 3-6

Table.A 15

Variables	Coefficient Descriptor	Time windows					
		1 day		3 days		5 days	
		Eq (8)	Eq (9)	Eq (8)	Eq (9)	Eq (8)	Eq (9)
Change of Degree (CD)	$\beta_{8,1}$or $\beta_{9,1}$	-0.01	-0.02	-0.05**	-0.07***	-0.09***	-0.08***
		(-0.4)	(-0.46)	(-2.51)	(-2.83)	(-5.81)	(-4.11)
Post-crisis dummy (dP)	$\beta_{9,2}$	--	0.007	--	0.07	--	0.007
			(0.45)		(0.45)		(0.46)
dP × CD	δ_9	--	0.01	--	0.06	--	0.07*
			(0.18)		(1.31)		(1.82)
Security Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes
Rating-level Control		Yes	Yes	Yes	Yes	Yes	Yes
Index Return Control		Yes	Yes	Yes	Yes	Yes	Yes
T		3914	3914	3914	3914	3914	3914
N		72	72	72	72	72	72
R2		0.23%	0.23%	0.23%	0.23%	0.24%	0.24%

Appendix 3-7

Table.A 16

		Time windows					
		1 day		3 days		5 days	
Variables	Coefficient Descriptor	Eq (3-10)	Eq (3-11)	Eq (3-10)	Eq (3-11)	Eq (3-10)	Eq (3-11)
Anticipated DE (ADE)	β_1	-0.07	-0.12	-0.09	-0.12	-0.12*	-0.16**
		(-0.51)	(-0.76)	(-1.18)	(-1.35)	(-1.95)	(-2.27)
Unanticipated DE (UDE)	β_2	-0.49***	-0.71***	-0.22***	-0.37***	-0.24***	-0.32***
		(-6.36)	(-7.50)	(-4.91)	(-6.61)	(-6.82)	(-7.29)
Post-crisis dummy (dP)	β_3	--	0.007	--	0.007	--	0.007
			(0.45)		(0.45)		(0.46)
dP × ADE	δ_1	--	0.18	--	0.12	--	0.17
			(0.62)		(0.71)		(1.22)
dP × UDE	δ_2	--	0.66***	--	0.43***	--	0.22***
			(3.99)		(4.50)		(3.00)
Security Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes
Rating-level Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes
Index Return Control		Yes	Yes	Yes	Yes	Yes	Yes
T		3914	3914	3914	3914	3914	3914
N		72	72	72	72	72	72
R2		0.24%	0.25%	0.24%	0.24%	0.25%	0.25%

Appendix 3-8

Table.A 17

Variables	Coefficient Descriptor	Time windows: 1 day, Index 1	1 day, Index 2	1 day, Index 3	3 days, Index 1	3 days, Index 2	3 days, Index 3	5 days, Index 1	5 days, Index 2	5 days, Index 3
		Equation (3-3): $Index_{i,t} = \alpha_i + \beta_{3-12,1} \times dE_{i,t} + u_{i,t}$								
Event dummy (dE)	$\beta_{3-12,1}$	-0.39***	-0.29***	-0.20***	-0.21***	-0.14***	-0.15***	-0.21***	-0.11***	-0.11***
		(-5.80)	(-33.30)	(-18.74)	(-5.34)	(-27.59)	(-24.52)	(-6.91)	(-26.77)	(-23.97)
T		3914	3914	3914	3914	3914	3914	3914	3914	3914
N		72	72	72	72	72	72	72	72	72
R2		0.3%	0.4%	0.2%	0.2%	0.3%	0.2%	0.2%	0.3%	0.2%
		Equation (3-4): $Index_{i,t} = \alpha_i + \beta_{3-13,1} \times dE_{i,t} + \beta_{3-13,2} \times dP_{i,t} + \delta_{3-13} \times \left(dP_{i,t} \times dE_{i,t}\right) + u_{i,t}$								
Event dummy (dE)	$\beta_{3-13,,1}$	-0.56***	-0.45***	-0.32***	-0.32***	-0.20***	-0.19***	-0.27***	-0.17***	-0.18***
		(-6.91)	(-42.32)	(-25.64)	(-6.95)	(-32.94)	(-25.77)	(-7.36)	(-34.05)	(-30.61)
Post-crisis dummy (dP)	$\beta_{3-13,2}$	-0.007*	0.0003	0.0004	-0.008*	0.0003	0.0003	-0.008**	0.000	-0.0001
		(-1.77)	(0.91)	(0.79)	(-1.93)	(0.61)	(0.52)	(-2.01)	(0.13)	(-0.18)
dP × dE	δ_{3-13}	0.54***	0.50***	0.41***	0.37***	0.20***	0.13***	0.18***	0.18***	0.20***
		(3.71)	(26.32)	(18.13)	(4.43)	(18.03)	(9.68)	(2.81)	(21.23)	(19.21)
T		3914	3914	3914	3914	3914	3914	3914	3914	3914
N		72	72	72	72	72	72	72	72	72
R2		0.3%	0.5%	0.3%	0.3%	0.4%	0.3%	0.4%	0.5%	0.4%
Security Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating-level Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Index Return Control		No	No	No	No	No	No	No	No	No

Appendix 4-1.1 The inference of Equation (4.2.7)

Equation (4.2.7) is a technical assumption regarding the CRA's adjustment of p_1 and p_2. The key principle of this assumption is to equate $P(S = G|SL = 1, CA = 1)$ and $P(S = G|SL = 0, CA = 1)$. According to the rule of conditional probability, if we have three events A, B and C,

$$P(A|B,C) = \frac{P(A,B,C)}{P(B,C)} = \frac{P(A,B)P(C|A,B)}{P(B,C)} = \frac{P(A)P(B|A)P(C|A,B)}{P(B,C)}$$
$$= \frac{P(A)P(B|A)P(C|A,B)}{P(B)P(C|B)}$$

Replacing A, B, C with S=G, SL=1(0) and CA=1 respectively, I have

$$P(S = G|SL = 1, CA = 1) = \frac{P(S = G)P(SL = 1|S = G)P(CA = 1|S = G, SL = 1)}{P(SL = 1)P(CA = 1|SL = 1)}$$
$$P(S = G|SL = 0, CA = 1) = \frac{P(S = G)P(SL = 0|S = G)P(CA = 1|S = G, SL = 0)}{P(SL = 0)P(CA = 1|SL = 0)}$$

For the numerators in both equations, the common factor $P(S = G)$ can be ignored. Besides, based on the non-biased assumption in Equation 4.2.9, $P(CA = 1|S = G, SL = 1) = P(CA = 1|S = G, SL = 0)$, so these two factors can be ignored. Therefore, to equate $P(S = G|SL = 1, CA = 1)$ and $P(S = G|SL = 0, CA = 1)$, what I actually need is

$$\frac{P(SL = 1|S = G)}{P(SL = 1)P(CA = 1|SL = 1)} = \frac{P(SL = 0|S = G)}{P(SL = 0)P(CA = 1|SL = 0)}$$

→

$$\frac{\tau_1\theta}{p_1[\tau_1\theta + \tau_2(1-\theta)]} = \frac{\theta(1-\tau_1)}{p_2[(1-\tau_1)\theta + (1-\tau_2)(1-\theta)]}$$

→

$$\frac{p_1}{p_2} = \frac{\tau_1[\theta(1-\tau_1) + (1-\theta)(1-\tau_2)]}{(1-\tau_1)[\tau_1\theta + \tau_2(1-\theta)]} \qquad (4.2.7)$$

Appendix 4-1.2 Inference of Equation (4.2.12)

$\mathrm{P(S = G|CA = 1)}$

$$= \frac{P(S = G, CA = 1)}{P(S = G, CA = 1) + P(S = B, CA = 1)}$$

$$= \frac{P(S = G, CA = 1, SL = 1) + P(S = G, CA = 1, SL = 0)}{P(S = G, CA = 1, SL = 1) + P(S = G, CA = 1, SL = 0) + (S = B, CA = 1, SL = 1) + P(S = B, CA = 1, SL = 0)}$$

$$= \frac{\theta\tau_1 p_1 + \theta(1-\tau_1)p_2}{\theta\tau_1 p_1 + \theta(1-\tau_1)p_2 + (1-\theta)\tau_2 p_1 + (1-\theta)(1-\tau_2)p_2}$$

→

$\mathrm{P(S = G|CA = 1)} - P(S = G)$

$$= \frac{\theta\tau_1 p_1 + \theta(1-\tau_1)p_2}{\theta\tau_1 p_1 + \theta(1-\tau_1)p_2 + (1-\theta)\tau_2 p_1 + (1-\theta)(1-\tau_2)p_2} - \theta$$

$$= \frac{\theta(1-\theta)(p_1 - p_2)(\tau_1 - \tau_2)}{\theta\tau_1 p_1 + \theta(1-\tau_1)p_2 + (1-\theta)\tau_2 p_1 + (1-\theta)(1-\tau_2)p_2} \qquad (4.2.12)$$

Appendix 4-2 Descriptive statistics of fundamental variables

Table A.18

Variable	N	Mean	Std Dev
Total Assets (thousand dollars)	10773	1905132.84	14983802.91
Total Debt to Total Asset (%)	9908	25.7862234	17.0716754
Financial Leverage (%)	9579	11.6971016	131.5634474
Return on Assets (%)	9691	2.3955979	5.4947532
Growth Rate of Assets (Quarterly, %)	9332	10.9630610	80.8996814
Total Investment to Total Assets (%)	9755	55.0474089	40.8825806
Asset Turnover (%)	9076	0.3217423	0.3700140
Sales to Total Assets (%)	9974	0.0779343	0.0942195

Appendix 4-3: Example of the identification of ‘lead-lag’ relationship between Moody’s and S&P/Fitch rating changes

Example 1:

Firm Bloomberg code: GAZP RM

Rating actions by Moody’s: Sep 8th, 2005, put into the possible upgrade list by Moody’s (a positive action)

Rating actions by S&P: Oct 13th, 2005, upgraded by S&P at 1 notch (a positive action)

S&P’s action occurs 35 days (<90) after the action of Moody’s so I identify this case as ‘Moody’s lead S&P’.

Example 2:

Firm Bloomberg code: GAZP RM

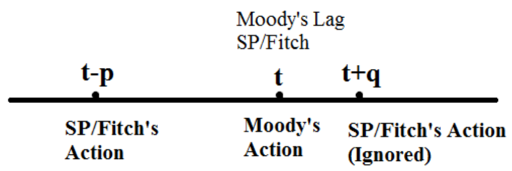
Rating actions by Moody’s: June 12th, 2012, downgraded by Moody’s at 1 notch (a negative action)

Rating actions by Fitch: May 21st, 2012, put into possible downgrade list by Fitch (a negative action)

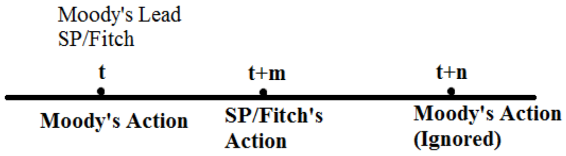
Fitch’s action occurs 22 days (<90) before the action of Moody’s so I identify this case as ‘Moody’s lag Fitch’.

Appendix 3B: Some complicated cases for identifying ‘lead-lag’ relationship between Moody’s and S&P/Fitch rating changes

If Moody’s takes actions at date t and no actions of Moody’s are taken during the period (t-90,t+90), S&P (or Fitch) take actions of same type at both dates (t-p) and (t+q), (p and q are smaller than 90), I identify the case as ‘Moody’s lag S&P or Fitch’ (just ignore the actions at date t+q);



If Moody's takes actions at both t and t+n (n<90), and S&P (or Fitch) have actions of same type at t+m (m<n) between t and t+n, I identify the case of date t as 'lead S&P or Fitch' and ignore the action of Moody's at t+n;



In some extreme cases, the two situations above happen simultaneously (the figure below demonstrates two scenarios). To deal with those cases, I regard the rating agency who takes the first action in certain time windows (90 days) as the one who always lead the other.